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Springback analysis in air bending process through experiment based artificial neural networks

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Abstract

Sheet metal bending is one of the most frequently used sheet metal forming processes in manufacturing industry. This study investigates bending parameters and springback phenomenon of a stainless-steel sheet in air bending process. In most of the applications, springback is determined either by trial and error procedures or by using numerical methods. Artificial Neural Network (ANN) approach has proved to be a helpful tool for the engineers. ANN is used in this study to predict the springback amounts of stainless steel sheets through experiment based networks. Air bending process is first modeled and analyzed by a commercial finite element code. Springback amounts for different sheet thicknesses and bend angles are computed. In addition to computational modeling, experimentation of the air bending processes is carried out and experimental results are used in artificial neural network development to show the feasibility of ANN based on experimentation. Experimental outcome is also used for validation of the FE analysis of the process, which demonstrates good agreement. It is observed that ANN can be applied effectively to determine springback in air bending process, which embodies significant potential to determine air bending process parameters for industrial applications such as punch stroke.

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1. Introduction

Several researchers have worked on the effects of springback phenomenon in various forming operations.Panthi et al. (2007) modeled sheet metal bending process with a large deformation algorithm based on total elastic – incremental plastic strain. They examined the effect of load on springback for different sheet thicknesses and different die radii. Esat et al. (2002) calculated the amount of springback, the total equivalent plastic strain and the equivalent von Mises stress distributions of different aluminum materials with different thicknesses in bending operations by commercially available finite element analysis (FEA) software. They compared the FEA results with empirical data.

Air bending is a similar process to V-die bending however differences in die geometry cause varied springback behavior in process. These differences and springback behavior of metals in air bending are investigated by many researchers. Fu et al. (2011) constructed a finite element model using Hill's quadratic anisotropic yield function under the conditions of plane stress and plane strain, respectively. They embedded the improved Hill's yield function into ABAQUS to model single-step air-bending along with semi-ellipsoid-shaped workpiece multiple-step air-bending tests for WELDOX700, WELDOX900 and OPTIM960 anisotropic sheets. They calculated springback, thickness strain along the transverse direction and part profiles in air bending. Wang et al. (2008) proposed a bending methodology to achieve more accurate final bend angles by controlling punch displacement. They estimated workpiece properties from measured loaded and unloaded bend angles and these estimated properties are used to determine the final punch position required to obtain the desired bend angle after springback. They made a series of experiments and compared the test results with their FE analysis results.

Prediction of springback with the help of artificial neural network (ANN) is a popular and controversial matter. Many research studies have been carried out related to this topic. Fu et al. (2010) developed a neural network algorithm for prediction of punch radius problem involving many parameters of air-bending forming. For minimizing the error between the predictive punch radius and the experimental one, they used a genetic algorithm (GA) to optimize the weights of neural network. They established 2D and 3D FEM with the predicted punch radius and other geometrical parameters of a tool. They showed that the punch design method is feasible with the prediction model of GA-neural network. Forcellese et al. (1998) investigated a neural network control system for the development of an intelligent air bending process. They especially focused on the training set size for predictive performances of the neural networks. They bent aluminum sheets which are in form of different thicknesses to obtain the database for training. They used their neural network model to predict other bent specimens and they compared the results.

2. Artificial Neural Network

Artificial neural networks (ANNs) are made of interconnecting artificial neurons which may share some properties of biological neurons. Neural networks learn by example like people. Neural networks possess the ability to model input-output relationship of data in a nonlinear fashion. Neural networks have been used in a broad range of applications including pattern classification, pattern recognition, optimization, prediction and automatic control.

Generally multi-layer neural network is used in the systems. A multi-layer neural network consists of an input layer, hidden layers and an output layer. The first layer is the input layer and it accepts the input data for training. Input layer consists of a number of neurons usually equal to the number of input. Hidden layers are between the input and output layer. Hidden layer receives the data from the input layer, then processes the data and finally sends a response to the output layer. Hidden layer consists of many computational neurons and transfer functions. Output layer consists of a number of computational neurons. In this study, multilayer feedforward backpropagation algorithm is used as ANN system algorithm. Log-Sigmoid function is used for transfer function, Levenberg-Marquardt is chosen as training function, and mean-squared error method is used for performance function in the system.

3. ANN development for air bending and results

In this study, firstly, experiments of the air bending processes are carried out and results of the experiments are compared with the results of FEA. Secondly, artificial neural network based on experimental results is developed. ANN is based on experimental results to show feasibility of ANN with experimentation. Experimentation is also used for validation of FE analyses of the process.

3.1. FEA and experimentation of air bending

In the FE simulations, air bending operations are considered as plane strain problems. Four-node quadrilateral plane strain elements are used in the software MSC.Marc 2010. Friction between sheet, punch, and die has been utilized by means of Coulomb's law, where the friction coefficient is taken as 0.05. In this study, steel sheets (SS 304) are assumed to be free of residual stresses before loading starts. Updated Lagrange procedure is preferred as an analysis option, which is employed in large strain and large displacement analyses.

In this case study, air bending is modeled and simulated for eight different bend angles and two different sheet thicknesses. Sheet thicknesses are 1 and 1.5 mm. For 1 mm sheet thickness, bend angles are 93.6°, 101.4°, 112.3° and 128.0°. For 1.5 mm sheet thickness, bend angles are 92.3°, 118.5°, 121.0° and 134.0°. The dimensions of the punch and die used in bending are illustrated in Figure 1. The steel sheet is placed on the die, and the punch moves vertically downward towards to sheet until the desired angle is achieved.

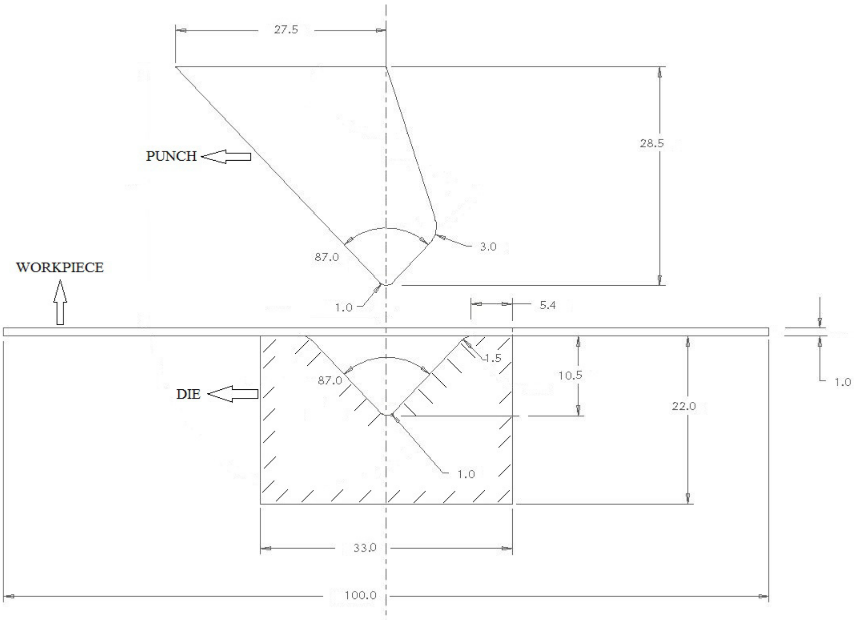

Fig. 1. Schematic view of experimental setup.

Plastic strain-true stress data is achieved by tension test. All steel sheets have the modulus of elasticity of 200 GPa and a Poisson's ratio of 0.3 and yield strength of 340 MPa. For elastic – plastic deformation behavior, strain hardening data is given in Table 1. In the tension test 18 specimens are tested and on the achieved results optimization is done to get precise results. The workpieces have the dimensions of 100×100 mm. Bend angles of sheets at fully loaded case are calculated with the help of digital angle measuring device which has a sensitivity of 0.1°. All experimental readings are conducted at least three times and experimental measurement error does not exceed 1% in all cases.

Table 1. Strain hardening data.

Plastic Strain (mm/mm)	True Stress (MPa)
0.0000	340
0.0513	410
0.0862	445
0.1040	467
0.1500	510
0.2000	550
0.2950	591
0.3560	610

In the case study for air bending of 1 mm steel sheets, the results gathered from the FEA and the experiments are provided in Table 2.

Table 2. FEA and experiment results for 1 mm steel.

		Part Angle (°)		Springback (°)	
Thickness (mm)	Bend Angle (°)	FEA	Experiment	FEA	Experiment
1.0	93.6	102.4	103.4	4.4	4.9
1.0	101.4	108.8	109.8	3.7	4.2
1.0	112.3	118.3	119.3	3.0	3.5
1.0	128.0	133.0	133.2	2.5	2.6

From Table 2, it is observed that springback amounts decrease as bend angle increases. Table 2 shows that the results of springback amount for air bending, the FEM results and the experimental results are close and in good agreement. This outcome supports the idea that FEM can be effectively used to simulate bending. In a similar manner, in air bending of 1.5 mm steel sheets case study, the results gathered from the FEA and the experiments are provided in Table 3.

Table 3. FEA and experiment results for 1.5 mm steel.

		Part Angle (°)		Springback (°)	
Thickness (mm)	Bend Angle (°)	FEA	Experiment	FEA	Experiment
1.5	92.3	98.1	98.6	2.9	3.2
1.5	118.5	122.5	123.1	2.0	2.3
1.5	121.0	124.8	125.4	1.9	2.2
1.5	134.0	137.4	137.8	1.7	1.9

From Table 3, similar to Table 2, it is observed that springback amounts decrease as bend angle increases. Table 3 also shows that the results of springback amount for air bending, the FEM results and the experimental results are close and in good agreement. This outcome also supports the assertion that bending operations can be simulated by FEM effectively, and therefore both FEA predictions and experimental results can be employed to construct ANNs.

3.2. ANN development of experimental air bending results

To predict springback amounts with ANN for air bending operations, an artificial neural network structure is developed which is based on experimental results. Three different training and three different testing data sets for air bending process are created. Training data sets are shown in Table 4. Constructed testing data sets are shown in Table 5.

Table 4. Training data sets.

First training data set			Second training data set			Third training data set		
Thickness (mm)	Bend Angle (°)	Springback (°)	Thickness (mm)	Bend Angle (°)	Springback (°)	Thickness (mm)	Bend Angle (°)	Springback (°)
1.0	93.6	4.9	1.0	93.6	4.9	1.0	93.6	4.9
1.0	112.3	3.5	1.0	101.4	4.2	1.0	112.3	3.5
1.0	128.0	2.6	1.0	128.0	2.6	1.0	128.0	2.6
1.5	92.3	3.2	1.5	92.3	3.2	1.5	92.3	3.2
1.5	121.0	2.2	1.5	118.5	2.3	1.5	118.5	2.3
1.5	134.0	1.9	1.5	134.0	1.9	1.5	121.0	2.2
						1.5	134.0	1.9

Springback depends on two independent parameters in each ANN system for air bending process and these parameters are thickness and bend angle. Constructed ANN systems combine these two different parameters and try to draw a general pattern to achieve the final springback amount.

Table 5. Testing data sets.

First testing data set			Second testing data set			Third testing data set		
Thickness (mm)	Bend Angle (°)	Springback (°)	Thickness (mm)	Bend Angle (°)	Springback (°)	Thickness (mm)	Bend Angle (°)	Springback (°)
1.0	101.4	4.2	1.0	112.3	3.5	1.0	101.4	4.2
1.5	118.5	2.3	1.5	121.0	2.2			

To investigate repeatability, accuracy and robustness of different ANN systems for the same database, three different training data sets and three different testing data sets are created and used in training part. Different hidden layer numbers, different training and testing percentages are tried and results are achieved. Results are shown in Table 6.

Table 6. ANN results.

ANN results for the first system			ANN results for the second system			ANN results for the third system		
4 Hidden Layers			4 Hidden Layers			3 Hidden Layers		
Thickness (mm)	Bend Angle (°)	Springback (°)	Thickness (mm)	Bend Angle (°)	Springback (°)	Thickness (mm)	Bend Angle (°)	Springback (°)
1.0	101.4	4.10	1.0	112.3	3.33	1.0	101.4	4.18
1.5	118.5	2.34	1.5	121.0	2.25			

Obtained ANN results are compared with experimental results, and relative percent errors are calculated, as given in Table 7.

4. Discussion

Table 7 clearly shows that the constructed ANN systems with the selected parameters are highly capable of predicting the springback amounts for the air bending process. The percentage error is between 0.48 and 4.86. It is observed that if the number of training input increases (Table 5), ANN system requires less hidden layers and converges quickly. Accuracy of the ANN system's result increases with increasing training input/testing input ratio as in third system in Table 7. Error of third system is less than errors of both first and second systems.

From Table 7, it is seen that different training sets with the same size (first and second systems) can be used for similar testing sets in the same database of springback results. Percentage errors of these two systems are close to each other. These results verify repeatability and accuracy of different ANN systems for the same database.

Table 7. Relative errors in percentage.

First System

		Springback (°)		
Thickness (mm)	Bend Angle (°)	Experiment	NN (4 Hidden Layers)	Error (%)
1.0	101.4	4.20	4.10	2.38
1.5	118.5	2.30	2.34	1.74

Second System

		Springback (°)		
Thickness (mm)	Bend Angle (°)	Experiment	NN (4 Hidden Layers)	Error (%)
1.0	112.3	3.50	3.33	4.86
1.5	121.0	2.20	2.25	2.27

Third System

		Springback (°)		
Thickness (mm)	Bend Angle (°)	Experiment	NN (3 Hidden Layers)	Error (%)
1.0	101.4	4.20	4.18	0.48

Table 7 emphasizes that developed ANN systems are feasible and robust. All three ANN systems give very close results for springback predictions of air bending models. Table 7 also shows that if the number of independent parameters in the system decreases, system converges to desired outputs more quickly.

5. Conclusion

The main aim in this study is to determine springback and predict the final part shape in air bending operations by the use of ANN algorithms based on experiments. Steel sheets with two different thicknesses; 1, and 1.5 mm are used in the finite element simulations and artificial neural network system based on experimental data for air bending process. Constructed ANN systems with the selected parameters are highly capable of predicting the final part shapes for air bending processes after springback. Constructed ANN systems predict springback amounts accurately. Accuracy of the ANN system result increases with increasing training input/testing input ratio as observed from the experiments of air bending. The system should also not be over trained. This can be decided during the ANN development process by trial-and-error sensitivity perturbation procedures.

Springback calculation using numerical methods, by trial and error procedures or with the help of handbook tables is a time consuming task. In this respect, Artificial Neural Network algorithm proves to be a useful tool to determine the springback amounts in air bending processes correctly and quickly. Also, different bending operations such as angular bending, hemming, U-bending may be analyzed through FEA and experimentation, and ANNs based on FEA or experimentation may be utilized to analyze more complicated bending operations consisting of several bent-up regions.

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