Using Neural Network and Genetic Algorithm for Spring Back Minimization in Sheet Metal Forming

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Abstract: The sheet metal bending is an important form of sheet metal forming process, widely used in various industrial applications. Furthermore, the spring back of sheet metal, which is defined as elastic recovery of the part during unloading, should be taken into consideration so as to produce bent sheet metal parts within acceptable tolerance limits. Spring back is affected by the factors such as sheet thickness, specimen orientation and depth of die. This study predicts and minimizes the responses of the sheet metal bending process using artificial neural network and genetic algorithm. Artificial neural network is getting wide popularity in recent years due to their ease, quickness and economy.

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1. Introduction

Spring back is a phenomenon that occurs in many cold working processes. When a metal is deformed into the plastic region, the total strain is made up of two parts, the elastic part and the plastic part. When removing the deformation load, a stress reduction will occur and accordingly the total strain will decrease by the amount of the elastic part, which results in spring back (DeGarmo et al., 1988). It plays an essential role in sheet metal forming processes in order to obtain a geometrically optimized shape. Accordingly the spring back prediction in sheet metal forming is of great significance in industrial applications. There are several parameters affecting spring back, such as sheet thickness, depth of die, specimen orientation and forming speed. Regarding the complicated and nonlinear relationship between the effective parameters in spring back phenomenon, having a theoretical model to perform spring back calculations is very challenging. Therefore, many researchers have employed finite element methods (FEM) and artificial neural network (ANN) approaches to propose specific models to control and predict the spring back. Due to the time-consuming and numerous runs in finite element method, ANN which overcomes the complexities of FEM is preferred in many cases.

Kinsey et al., (2000) discussed the implementation of ANN approach for the first time. They used ANN to predict spring back in free V-bending sheet metal forming. Kim and Kim (1999) employed finite element simulations and ANN to predict spring back. Karafillis and Boyce (1992, 1996) performed Spring Forward method in designing dies to obtain the desired final shape. Liu et al. (2007) used a GA-trained neural network to develop a model for spring back prediction in U-shaped bending. Ruffini and Cao (1998) implemented a neural network control system to reduce spring back in a stamping process of aluminum. Sun et al. (2006) used a closed-loop control system to develop a method for evaluating spring back during metal forming process. Kazan et al. (2009) used ANN to propose a prediction model for spring back in wipe bending process, where the training data for the neural network were calculated using finite element methods.

In the present study, the spring back angle in typical U-die bending process is minimized using the genetic algorithm (GA) (Goldberg, 1989). Because the calculation of spring back by actual experiments for any different value of effective parameters isn’t economically reasonable and is in some level impossible to perform, we employed the powerful ANN approach to find the nonlinear relationship between effective parameters and spring back angle. In this regard, to obtain the relationship between different parameters such as sheet thickness, depth of die and specimen orientation and spring back angle value, experimental tests were performed. Then, concluding results were used to train the appropriate neural network in order to predict spring back angle for other parameter values.

2. Artificial Neural Network Approach

ANN approach is a simulation of human brain in processing the mathematical information. ANN is consisted of a group of neurons (processor elements) and their connector linkages with adjustable weights related to the governing conditions of the problem.

The neural networks have three kinds of layers, namely an input layer, hidden layers and an output layer. The obtained data from the experiments enter the neural network through the input layer. Layers included between the input and output layers are called “Hidden Layers”. These layers receive the data from the input layer and send them to the output layer after processing them. Receiving data from the hidden layers, the output layer makes a vector as the output of neural network (Figure 1).

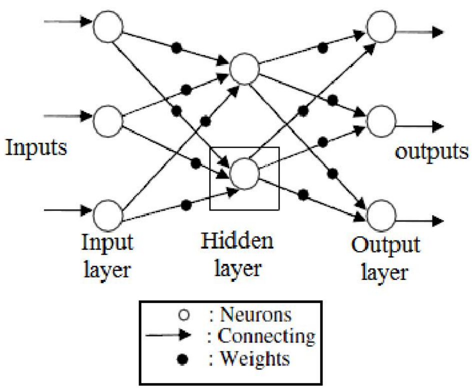

Figure 1. The architecture of an artificial neural network

36 Experimental tests were performed to find the required data for training the appropriate ANN as well as to predict and control the spring back angle (Table 1). Accordingly, several aluminum sheets with the thicknesses of 0.5, 1, 1.5 and 2 millimeters were cut at different orientations to the rolling direction (0, 45 and 90 Degrees). Consequently, the U-die bending experiment was performed for U-die depths of 20, 25 and 30 millimeters to find the spring back angles with the die shown in Figure 2.

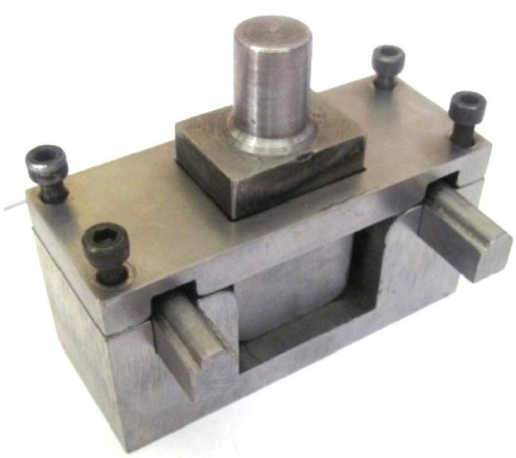

Figure 2. An overview of the die used for U-die bending experiment

Table 1. Input data to the neural network using the experimental results (NS: sample number, t: thickness, D: die depth, θ: specimen orientation to the rolling direction, SB: spring back angle)

NS	t (mm)	D (mm)	θ (deg)	SB (deg)
1	0.5	20	0.0	11.9
2	1	25	45	7
3	0.5	30	90	4.2
4	2	30	45	1.7
5	0.5	25	90	12.5
6	1	30	0.0	4
7	1.5	20	90	7.8
8	0.5	30	45	10.7
9	1	20	0.0	8.9
10	1.5	25	45	7.1
11	0.5	20	45	14
12	1	25	90	7.4
13	1.5	30	0.0	3.5
14	2	20	90	3
15	1	30	45	6
16	1.5	20	0.0	5.6
17	2	25	45	2.4
18	0.5	30	90	11.5
19	1.5	25	90	7.9
20	2	30	0.0	1.5
21	0.5	20	90	15.2
22	1	25	0.0	5.4
23	2	25	0.0	2.2
24	0.5	25	45	11.6
25	1	30	90	6.5
26	1.5	20	45	7
27	2	25	90	2.8
28	0.5	30	0.0	6.1
29	1.5	25	0.0	6.3
30	2	30	90	2
31	1	20	45	10.4
32	2	20	0.0	2.5
33	0.5	25	0.0	8.4
34	1	20	90	11.2
35	1.5	30	45	3.8
36	2	20	45	2.7

According to the fact that applying a 2-layer neural network (with one hidden layer) enables us to model any nonlinear relationship with a desired accuracy (Hormik et al., 1989), a 2-layer neural network was used in the present paper. Sheet thickness, die depth and specimen orientation to the rolling direction are considered as the ANN inputs while spring back angle acts as the ANN output. Considering the dependence of neural network to how to select the test and training data, two different sets of test and training data were chosen to train two different types of neural networks. In the first set, samples 33 through 36 and in the second set, samples 4, 33, 34 and 35 in Table 1 was chosen as the test data while other entries were selected as training data. Furthermore, various neural networks were trained for these 2 sets of input data where the optimum network was obtained with 7-Neuron and 6-Neuron hidden layers for Set 1 and set 2, respectively. The architecture of the ANN along with the activation functions used in the chosen models is presented in Table 2.

Table 2. ANN architecture and functions

Network	Feed-forward back propagation
Training method	Supervised training
Transfer function	Log-Sigmoid function
Training function	Levenberg–Marquardt
Learning function	Gradient descent
Performance function	Mean squared error

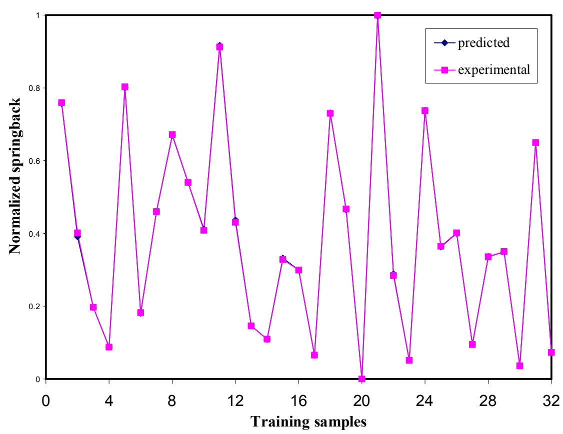

Figure 3. Comparison of experimental and predicted spring back values by ANN for train data (type 1)

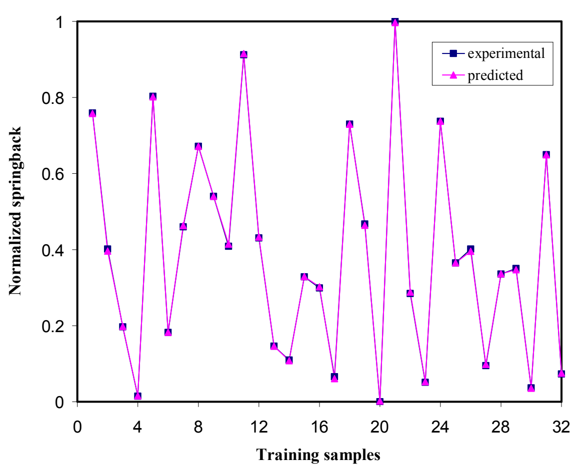

Figure 4. Comparison of experimental and predicted spring back values by ANN for train data (type 2)

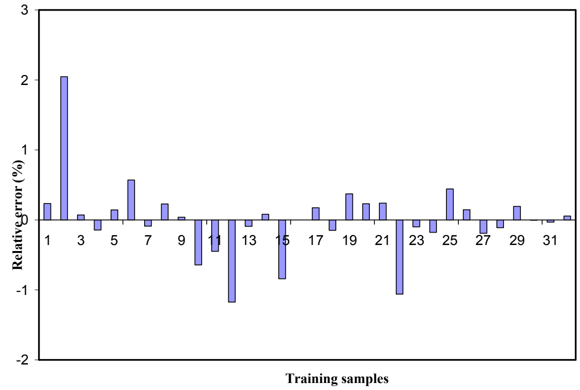

Figure 5. Relative error of ANN training samples (type 1)

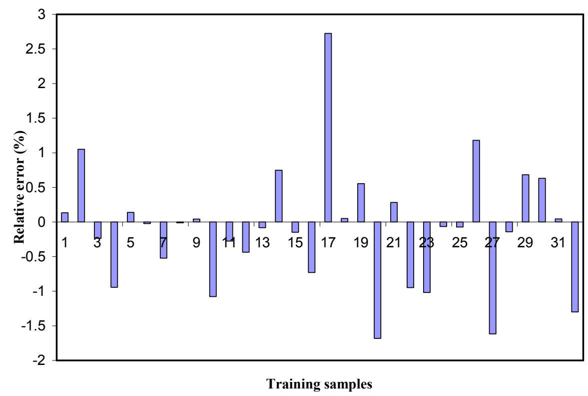

Figure 6. Relative error of ANN training samples (type 2)

A comparison of predicted values by ANN with experimental data which were used to train type 1 and type 2 neural networks is presented in Figures 3 and 4. In Figures 5 and 6, the relative error for training data of type 1 and type 2 neural networks is shown, respectively. Moreover, the relative error between predicted values of spring back and experimental test samples are presented for type 1 and type 2 neural networks in Figures 7 and 8, respectively.

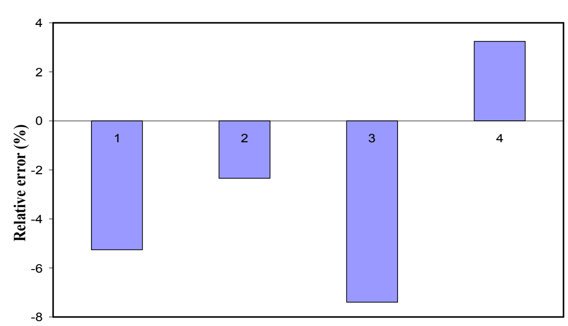

Figure 7. Relative error of ANN test samples (type 1)

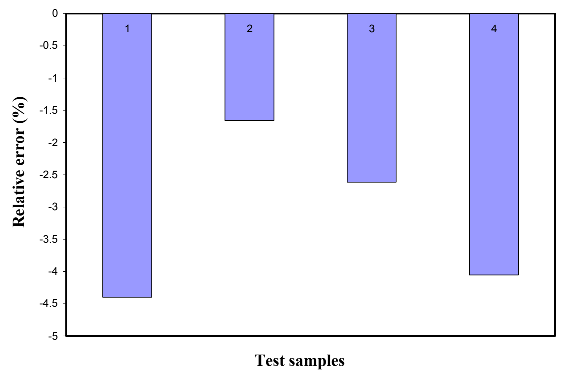

Figure 7. Relative error of ANN test samples (type 2)

It can be observed that the errors between experimental and predicted values by ANN for train samples are insignificant, therefore it is concluded that the neural network has been extended well for both types.

3. Spring Back Minimization Using GA

Table 2. The results of spring back minimized angle using GA

Neural Network	Type 1	Type 2
Sheet Thickness	2	1.99
Die Depth	30	29.99
Specimen Orientation	0.006	9.08
Spring back	1.44	1.55
Initial population	20	20
Iteration	57	51

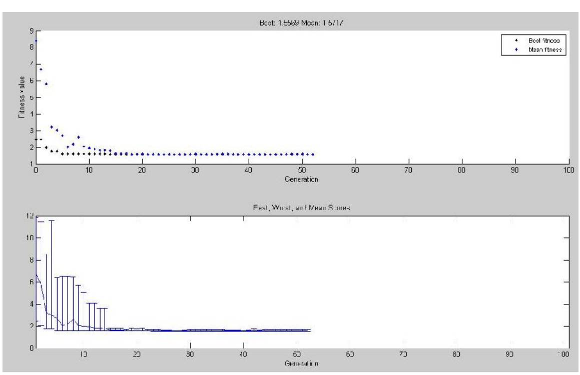

Figure 9. The process of reaching to minimized spring back angle (type 1)

After finding the appropriate trained ANN for spring back angle prediction in terms of different aforementioned parameters, one can minimize the spring back angle using GA algorithm. The variation range for the effective variables was within (0.1,2) millimeters for sheet thickness, (20,30) millimeters for die depth and (0,90) degrees for the specimen orientation to the rolling direction. The results of spring back minimize angle using GA in conjunction with the trained ANN are provided in Table 3 for both types of neural networks.

The process of reaching to the minimized spring back angle is shown in Figures 9 and 10 respectively.

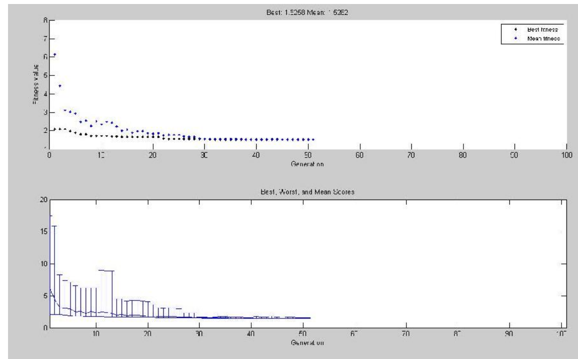

Figure 10. The process of reaching to minimized spring back angle (type 2)

4. Discussions

It can be seen that GA converged to a desired value for effective parameters. As the algorithm converges to the minimized value for spring back, it can be concluded that the ANN has provided precise values of fitness function for all ranges of different variables. This implies the good training of the neural network.

From the results provided in Table 3, it is observed that the minimized spring back values obtained from employing GA in conjunction with both neural networks were the same. However, the ANN can be trained with more training samples in the vicinity of minimized value, or with less training samples while checking the generalizability by choosing test data in that vicinity. In the current paper the aforementioned procedure was employed by using both training alternatives and same minimum results were reached. Therefore, even if we don't have the final minimum range, we can rely on our neural network by choosing the appropriate test samples providing that the generalizability of the network is completely met. Regarding the results of the performed experiments and the minimum results for spring back angle obtained from GA, it can be inferred that choosing a thicker sheet, deeper depth and smaller specimen orientation to the rolling direction, one can obtain a smaller spring back angle.

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