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Original Article

Springback and sidewall curl prediction in U-bending process of AHSS through finite element method and artificial neural network approach

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Abstract

Advanced high strength steels (AHSS) have been used extensively in the automotive industry to reduce weight and fuel consumption. However, increasing the strength of a material leads to the reduction in formability and a high degree of springback. Moreover, sidewall curl has been detected from U-bending operations of AHSS which caused problems in the assembly line. The aim of this research is to compare the efficiency of springback and sidewall curl prediction of AHSS grade SPFC980Y in the U-bending process by the finite element method and artificial neural network approach. Input data for the prediction consisted of punch radius (R_p), die radius (R_d), and blank holder force (F_b). The back propagation neural network model was trained by the springback values from a U-bending die experiment with 27 conditions. Efficiency estimations of springback and sidewall curl prediction were considered from the root mean square error (RMSE). The results showed that the finite element method for springback and sidewall curl were 0.104 and 0.092, respectively.

Keywords: springback, U-bending, AHSS, FEM, ANN

1. Introduction

Bending is a basic process of sheet metal forming and a very important application in the automotive industry. A big problem in the bending process is an unsatisfactory shape caused by the elastic recovery of the internal stress during unloading. There are various types of high strength steels

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(HSS) and advanced high strength steels (AHSS) used for automobile parts. Automakers can reduce the thickness of a material to make parts while the crashworthiness performance remains which contributes to weight reduction and reduced fuel consumption. However, an improvement of strength leads to a point of unacceptable shape (Matsumura *et al.*, 2005; Mori *et al.*, 2007; Yamano *et al.*, 2005; Yoshida *et al.*, 2005). In the forming process of a hat-shaped part in a U-bending die, initially the sheet metal is held with blank holders followed by drawing into the die cavity by a moving punch. When the punch and the die are removed, the two phenomena that occur on the formed part are springback and sidewall curl.

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Many investigations have focused on the prediction of springback in the forming of HSS and AHSS sheet using the finite element method (FEM). Accuracy of springback simulation requires a material model which can accurately describe the complex material behavior at unloading. To improve springback and sidewall curl prediction, a novel approach to model the Bauschinger effect was developed and implemented in the commercial AutoForm code with the kinematic hardening model (Sresomroeng et al., 2011). Lee et al. (2011) accepted the results of the springback predictions for DP590 by using the kinematic hardening model. Chen et al. (2007 reported that sidewall curl was very sensitive to the contact condition in the simulation and that hard contact was preferred for HSS. Gomes et al. (2005) and Lee et al. (2012) used NUMISHEET'93 software to investigate the variation of springback in HSS due to material anisotropy. All of the predicted springback values were in good agreement with the experimental data. The results not only showed discrepancies between springback predicted by the various material models, but also showed the variability of springback with respect to the orientation of the anisotropic steel sheet according to the work of Taherizadeh et al. (2009). Livatyali et al. (2102) evaluated the amount of springback using finite element code DEFORMTM. The results had very good agreement with the experimental results. Sresomroeng et al. (2010) investigated the influence of the bending die clearance on the springback values of HSS using the commercial finite element code DEFORM 2D. The results showed that die clearance strongly affected the springback values of the bent parts and the amount of springback increased with the increase in die clearance. However, when the value of the die clearance was less than the value of the sheet thickness, spring-go would occur at the bend angle. Huang et al. (1995) used elasticplastic finite element computer code to explore the effects of die clearance, die radius, and the coefficient of friction (μ) on the final shape after unloading. The results coincided with the work of Cho et al. (2003) which used thermo-elastoplastic. Occurrence of the springback phenomenon obviously increased as die clearance and µ increased. Samuel et al. (2000) predicted springback and sidewall curls in the U-bending process by the incremental elastoplastic finite element. Springback in the U-bending process increased with the punch radius and depended on the blank holder force. Lee et al. (2007) studied spring-back in sheet metal flange drawing using commercial code LS-DYNA3D. The results showed that the order of strong factors influencing springback were punch radius > die radius > blank holder force > supporting-force per unit width > lubrication. Unless the FEM is used to predict the springback value, a technique based on the artificial neural network approach is reported to solve the problem of springback and it has the advantage of better economics compared with FEM (Baseri et al., 2011; Liu et al., 2007; Sharad et al., 2014; Songkroh et al., 2015). However, few research reports predict springback with artificial neural networks (ANN) and no work has predicted sidewall curl in forming AHSS with ANN.

Since the cost of FEM software is relatively high and the ANN technique has the ability to solve non-linear problems, ANN could be an alternative tool to predict springback and sidewall curl values in bending AHSS parts if ANN is nearly as efficient as the FEM technique. The purpose of this research is to compare the efficiency of springback and sidewall curl prediction of AHSS in the U-bending process by FEM and ANN. The advantage of FEM is to investigate the final shape of an AHSS part after unloading by using various process parameters. For verification of the FEM model, experimental values for springback and sidewall curl from a U-bending die test were compared with the predicted values from the simulation model. The efficiency estimations of springback and sidewall curl were predicted between FEM and ANN by considering from the root mean square error (RMSE).

2. Experimental and Methodology

2.1 FEM conditions

The FEM was performed using AutoForm-Incremental^{plus} software. The simulation model with geometries of tool and initial sheet blank are given in Figure 1. An AHSS cold rolled sheet of 1.4 mm in thickness, grade SPFC980Y (JIS), was used as the blank sheet material. The initial rectangular blank size of 210 mm in length and 50 mm in width was employed. The flow stress of the sheet material was obtained by a tensile test and expressed with the standard power law model (Table 1).



Figure 1. Hat-shaped simulation model.

Table 1. Input data used for simulation with FEM.

Input data	Description
Material properties	Tensile strength = 1026 MPa Yield strength = 714 MPa $\overline{\sigma} = K \varepsilon^n$, where $K = 1408$ MPa and $n = 0.0891$ Normal anisotropy = 1.05
Coefficient of friction Element formulation Number of elements Layer number Kinematic hardening: (<i>K</i>)	0.15 Elastic-plastic shell Auto 11 (for spring-back problem) 0.002

Springback and sidewall curl can be affected by many factors, such as type of material, material thickness, bending radius, and die radius (Schuler, 1998). In this work, the influence of three parameters, which consisted of punch radius (R_p) , die radius (R_d) , and blank holder force (F_b) on the deformation behavior, were explored. The variations of those parameters used in this work are listed in Table 2.

Table 2. Process parameter variations.

Process parameter	Values
Punch radius; R_p (mm)	2, 5, and 10
Die radius; R_d (mm)	2, 5, and 10
Blank holder force; F_b (kN)	5, 10, and 20

2.2 Experimental conditions

A U-bending die experiment was conducted to verify the results of the springback and sidewall curl simulation model. The initial rectangular blanks of 210 mm in length and 50 mm in width were bent into hat-shaped parts. Experiments were carried out using the U-bending die on an 800-kN hydraulic press machine (Figure 2).



Figure 2. Outline of the U-bending die.

Ram speed was set at a constant 10 mm/s. A load cell and linear variable differential transformer were mounted to observe the force-travel diagram in real time. The width of the punch was 45 mm and the die clearance was 1.4 mm (one side) which was the same as the sheet thickness. The values of the punch radius, die radius, and blank holder force used in the experiments are shown in Table 2. There were 27 conditions for the U-bending die experiment. Thirty blank sheets of AHSS grade SPFC980Y were bent in each of the conditions. The amounts of springback and sidewall curl of the parts after bending were detected by a Mitutoyo profile projector. The results of springback and sidewall curl were then calculated as averages.

2.3 ANN methodology

In this study a back-propagation (BP) ANN was used to predict the springback and sidewall curl in the Ubending process. The BP-ANN is a multiple-layer network with an input layer, an output layer, and some hidden layers between the input and output layers. The input layers were R_p , R_d , and F_b . The output layers were springback and sidewall curl. The developed springback model and sidewall curl model were trained with the results obtained from the U-bending die experiment and used to predict the springback and sidewall curl for AHSS grade SPFC980Y (1.4 mm thick). Before the BP-ANN can be trained, it is important to normalize the input data and output data or target data to produce suitable data by normalizing the data to a value between 0 and 1 using the following equation:

$$X_n = \frac{X - X_{max}}{X_{max} - X_{min}} \tag{1}$$

where X_n is the normalized value, X is the curtain value, X_{max} is the maximum input value, and X_{min} is the minimum input value.

K-fold cross validation and the leave-one-out method were used to select the most appropriate data for training the BP-ANN. The data from the U-bending die experiment were separated into three sets as nine pieces of data per set. Two sets are required for training. The other set was used 27 times for the tests (Figure 3). Then the training set was selected to develop the BP-ANN model by the minimum of mean square error (MSE) or an acceptable small value. The results of the tests showed that the data provided by Loop 14 and Loop 23 had minimal MSE for the prediction of springback and sidewall curl. Consequently, those sets were selected and used for training and testing. The BP-ANN model structure of 3 layers for this study is shown in Figure 4 and include:

1) Layer 1: an input layer that consisted of input data as R_p , R_d , and F_b .

2) Layer 2: a hidden layer that consisted of 3 neurons using the sigmoid function to transfer data between nodes in the hidden layer.

3) Layer 3: an output layer that consisted of only 1 neuron (spring-back or sidewall curl value) using linear transfer to transfer data to an output space.

A BP-ANN model was used to determine the parameters from the experiment that included the learning rate equal to 0.2 and the error rate equal to 0.01. The result of the BP-ANN was a learning amount of 38 rounds for springback prediction and 36 rounds for sidewall curl prediction until convergence.



Figure 3. Collecting data with leave-one-out and K-fold cross validation methods.



3. Results and Discussion

To obtain the influence of the punch radius (R_b) , die radius (R_d) , and blank holder force (F_b) , the U-bending die experiment was performed several times at the process parameters. The results were plotted on a graph. The springback decreased as the punch radius decreased (Figure 5). On the other hand, the springback decreased as the value of blankholder force increased. The results were in good agreement with Samuel *et al.* (2000) and Lee *et al.* (2007). The sidewall curl decreased as the blank holder force and die radius increased (Figure 6).



Figure 5. Spring-back results.



Figure 6. Sidewall curl results.

The simulation model was verified by the maximum bending force and the final shape of the part. The U-bending die testing (with $R_p = 2$ mm, $R_d = 5$ mm, and $F_b = 10$ kN) required 28.69 kN to bend an AHSS hat-shaped part, while the simulation model indicated a maximum bending force of 29.78 kN. The final shapes of the experiment and FEM are shown in Figure 7. These confirmed that the numerical results agreed well with the experiment.

Figure 8 and Figure 9 show a comparison of the experimental results and the values which were predicted by the selected network and simulation model via FEM. Good agreement between the BP-ANN, FEM, and experimental verifications was demonstrated in those bending conditions. Therefore, a BP-ANN can be used to predict in a wide range of U-bending processes. However, the RMSE values of BP-ANN were 0.124 and 0.102 for springback and sidewall curl prediction, while the FEM showed 0.104 and 0.092 for springback and sidewall curl prediction, respectively.



Figure 7. Final shape of the experiment and FEM.



Figure 8. Comparison of the spring-back values obtained from actual measurements, BP-ANN, and FEM predictions.



Figure 9. Comparison of the sidewall curl values obtained from actual measurements, BP-ANN, and FEM predictions.

4. Conclusions

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A U-bending die experiment was conducted to investigate the influence of punch radius, die radius, and blank holder force on the springback and sidewall curl value of AHSS grade SPFC980Y. Also the results from the U-bending die experiment were used to verify the springback and sidewall curl results by FEM and BP-ANN prediction. From the results, it can be concluded that:

1) Springback decreases with an increase in the blank holder force. On the other hand, springback increases by increasing the punch radius.

2) Sidewall curl decreases with an increase in the blank holder force and die radius.

3) Springback prediction by the BP-ANN prediction model and FEM simulation model had good results compared with springback in the U-bending die experiment.

4) Prediction of sidewall curl by the BP-ANN prediction model and FEM simulation model had good results compared with the sidewall curl in the U-bending die experiment.

5) Efficiency of the BP-ANN for springback and sidewall curl prediction depends on collecting the appropriate data for the learning of the neural network.

6) In this work the FEM had greater efficiency than the BP-ANN and had the lowest RMSE values compared to the BP-ANN.

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