Prediction springback of sandwich sheets using Finite Element Analysis and Artificial Neural Network Approach

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***Abstract:***

The main objective of this study is to obtain a model that quickly predicts springback in air bending process of thick sandwich sheets. Thus, in this paper, the springback behavior of sandwich panels is investigated by using numerical simulations for different punch radius, die opening, and foam thickness. In addition, the Artificial Neural Networks method (ANN) was used in order to obtain a model to easily predict springback in air bending process of thick sandwich sheets. Based on 27 cases analyzed using finite element method, a neural network was trained. The ANN model was based on a multilayer feed forward topology and trained with LM back propagation algorithm with 12 neurons. The results of ANN model are compared with numerical results, and show a very good agreement.

**Keywords:** Sandwich plate, springback, artificial neural network (ANN), numerical simulation, bending.

1. **Introduction**

Sandwich plates are increasingly used in a wide range of industrial products varying from aerospace, shipbuilding, external and internal walls of industrial buildings, and automobiles to simple home appliances due to the properties such as lightweight, vibration reduction, acoustic noise damping, and heat insulation [1-4]. The understanding of sandwich behavior under bending and subsequent springback is extremely important for the design and manufacturing of these engineering structures. Modern sandwich plates are often composed of skins with high bending stiffness enclosing a lightweight core having a higher thickness than the skins [5-8]. The skins are generally distinguished by their low thickness and high rigidity. Many types of skins have been used, such as metal (steel, Aluminum) [9], composite laminate (carbon/epoxy, Fiberglass/epoxy) [10], wood, or thermoplastic plate [11]. The core can be made of balsa wood, closed-cell polymeric foam [10] or honeycomb structures [6].

An accurate modeling of metal deformations including springback is one of the most important issues in the industrial setting. In material forming, quantitative evaluation of the springback phenomenon is very important. The sandwich sheets exhibit more complicated bending and springback behavior due to substantial differences in mechanical properties between the core and the skin sheet. In order to improve geometrical accuracy of formed parts, bending parameters should be suitably selected to compensate the springback effect. In particular, the sandwich geometry, the mechanical properties (thickness, yield strength, Young’s modulus, etc.), the tooling geometry (punch radius, die radius, die opening, etc.) and the process parameters (punch stroke, punch velocity, etc.) have considerable influence on springback. A number of researchers have studied the analytical model based on the material properties and geometrical parameters to predict springback (Mohamadi et al. [12], Liu et al [13], Ouled Ahmed and Chatti [14]. Mohamadi et al. [12] proposed analytical models to obtain springback of Al/PP/Al sandwich in air bending test. They assumed that the distribution of the bending moment is linear along a sandwich part and the highest bending moment is located at the punch-sheet contact zone. They established that springback depends on wrap around the punch which is estimated by an iterative method. Liu et al [13] developed an analytical expression of springback angle of aluminum-polymer sandwich panels in air bending process. They proposed a model through analyzing the strain and stress distributions of skin sheet and core materials. More recently, O.Ahmed and Chatti [14] proposed semi analytical approach based on using mechanical parameters calibrated from the experimental load-displacement data of the bending process. They found that the semi-analytical predictions of springback are in good agreement with the experimental ones. Numerical methods have been widely used to predict springback. Various numerical parameters have been investigated to study their effect on springback prediction [15-19]. Traditional trial and error methods are time consuming and expensive, while the development of theoretical models for springback/bend force is difficult and cumbersome due to the complexity of sheet bending process. Consequently, an empirical model developed based on experimental research is more useful in industrial applications. The empirical modeling techniques namely response surface methodology (RSM) and artificial neural network (ANN) become more and more considered as an engineering design in industrial application. As a consequence, many prediction approaches have been proposed. Very few literatures are available for the prediction of springback of sandwich panels in air bending using this prediction tools.

O.Ahmed and Chatti [20] applied RSM technique to predict springback and finite element simulation of steel/polyurethane/steel sandwich panels in air bending process of using punch radius length between supports and thickness foam core as inputs. D.Vasudevan1and R.Srinivasan [21] applied the artificial neural network (ANN) and response surface methodology (RSM) approaches to predict springback and bend force in air bending of electro galvanised steel sheets and the models are compared based on their prediction performance. They used ANN model based on a multilayer feed forward topology and trained with LM back propagation algorithm. They found that the performance of the ANN model for predicting springback and bend force was found to be better than RSM models. Fei Han et al [22] proposed a method combining finite element simulation and ANN to establish a relationship between springback and processing parameters. Pathak et al [23] used finite element simulation and ANN technique to predict springback of metal sheet in air bending process considering sheet thickness and die radius as input parameters. They observed that the neural network gives quite close predictions of sheet forming responses.

Based on the aforementioned literature, while there are many studies devoted to bending process and springback of thin metallic sheet, there are not studies that address springback prediction of thick sandwich panel using Artificial neural networks methods ANN. Consequently, the aim of the present paper consists in predicting the springback of steel/ polyurethane (PUR)/steel sandwich panels in air bending process using the ANN approach. The obtained springback predictions by numerical simulations and ANN approach are compared.

1. **Experimental procedures**

In this study, we used a sandwich plate obtained by the injection method consisting of a polyurethane foam core (density of 40 kg/m3) and galvanized steel skins. Compression and tensile tests were carried out to determine the foam core and the skin mechanical properties respectively by using a screw driven MTS Insight universal testing machine equipped with a 200 kN load cell. The mechanical properties of the polyurethane foam and the steel skin were experimentally obtained and reported in table 1.

**Table 1**: Mechanical properties of the steel skin and the polyurethane foam core

|  |  |  |
| --- | --- | --- |
|  | Steel skin | Polyurethane foam core |
| Density[kg/m3] | 7800 | 40 |
| Yield stress0 [MPa] | 440 | 0.41 |
| Young’s modulus E [MPa] | 200000 | 3.31 |
| Poisson’s ratio | 0.3 | 0.4 |
| Strength Rm [MPa] | 453 | 0.53 |

Flexural strength was determined for all the specimens, using three-point bending test method. Tests were performed using MTS Insight universal testing machine equipped with a temperature controlled chamber. Data acquisition is performed with the TestWorks4 software that records the displacement versus force. Three-point bending tests followed the standard ASTM D 790. Subsequent tests are performed with a displacement rate of 3 mm/min. The length and width of the specimens were 500 and 50 mm respectively. The punch stroke was 30 mm. Notice that, in order to get reliable results, six specimens were experienced for every case.

1. **Finite element analysis**

Implicit finite element analysis was used to simulate the three-point bending and springback of steel/ polyurethane PUR/ steel sandwich panels using ABAQUS 6.14 software package.

Due to the material symmetry, only a half of the geometry was modeled. Punch and die were modeled as analytical rigid bodies. Figure 2 shows the FEM assembly used for the simulations. Mesh sensitivity analysis was performed to attain enough mesh density. 20 elements through thickness for each layer were ascertained as enough number of elements. To ensure more accurate results, the geometry is sufficiently refined, in particular, at the vicinity of the tools contacts. The 4-node bilinear plane strain quadrilateral, reduced integration, hourglass control element (CPE4R) is used. Coulomb friction law with the coefficient of 0.1 was assumed for interactions between punch and die contact surfaces with the sandwich panel. It is of importance to notice that the experimental data in terms of stress vs. strain, obtained from the tensile and the compressive tests, for the skin and the foam respectively, were used in the finite element analysis in order to get more accurate results. The punch moves downwards in order to bend the plate until reaching a full punch stroke of 30 mm. Subsequently, the tools are removed and springback can be predicted by measuring the difference between the depth of the sandwich plate underneath the punch noise before and after removing the punch. Steel skins with the thickness of 0.5 mm and polyurethane foam with the two thicknesses (e) of 40 and 60 mm were used for the preparation of sandwich sheet. Three-point bending tests were executed by varying the following process conditions: using three punch radii (Rp) of 82, 102 and 115 mm, and applying three die opening (L)of 200, 250 and 300 mm.

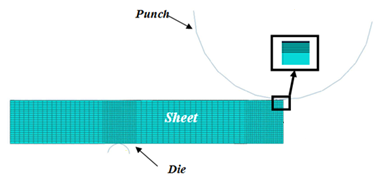


Figure 2: FE model of three-point bending process.

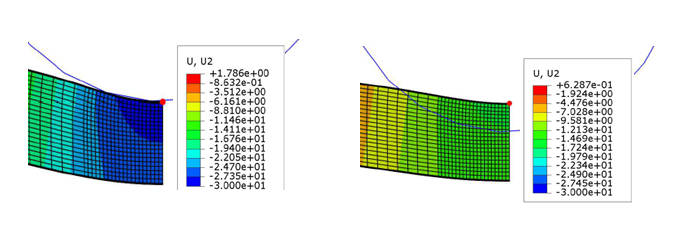
Figure 5 shows the evolution of the load as a function of the punch displacement obtained from experiment and numerical results with a width of 50 mm and foam thickness of 40 mm, for a distance between supports of 300 mm and punch radius of 82mm. This figure shows that the predicted punch loads have a good agreement with the experimental results which validate the numerical analysis.

Figure 5: Experimental and numerical bending plots (L= 300 mm; Rp=82mm; e=40mm).

The difference between the depth of the sandwich plate before and after removing the punch is obtained numerically in order to get the springback amount (∆Yp) (eq.1). One point is considered in the punch tip- sandwich plate contact zone to compute the depth of sandwich plate as shown in Figure 6. This procedure was applied in both forming and springback stages for the same sections.

 (1)

where Yf denotes the final displacement of the sandwich after removing the punch.



(a) (b)

**Figure 6**: Depth of sandwich plate calculation (a) before unloading, (b) after unloading.

Table 3.8 gives the numerical prediction and the experimental results of springback. From this table, it can be inferred that the calculated errors are between 5.3% and 18.3%. The errors can be assessed as generally acceptable and the validity of the model can be defined as satisfactory.

**Table 3**: Comparison of numerical and experimental results of springback.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Test N°** | **e (mm)** | **L (mm)** | **Rp (mm)** | **∆Yp (mm) FEM** | **∆Yp (mm) EXP** | **Error (%)** |
| 1 | 40 | 200 | 82 | 10.49 | 12 | 12,58 |
| 2 | 40 | 250 | 82 | 12.25 | 15 | 18,33 |
| 3 | 40 | 300 | 82 | 14.09 | 16 | 11,93 |
| 4 | 40 | 300 | 102 | 14.25 | 17 | 16,176 |
| 5 | 60 | 300 | 82 | 13,25 | 14 | 5,35 |

1. **ANN modelling**
   1. **ANN Approach**

Artificial Neural Networks have emerged as a new branch of computing, which leads to the resolution of problems encountered in the modeling and optimization of several processes. They showed a remarkable performance for modeling linear relationships and complex nonlinear. This mathematical tool is particularly useful for the simulation of any correlation that is difficult to describe with physical and mathematical models due to the ability to learn from examples. It is one of the most powerful tools for solving engineering design problems and minimizing errors in experimental data. Neural networks have been inspired both by human biological neural networks systems and mathematical theories of learning, processing and control of information.

A multi-layer neural networks architecture consists of an input layer, one or more hidden layers and an output layer. Figure 7 shows the basic structure of an artificial neuron. The input layer X1, X2, X3 …Xi is the layer that receives input data and after sends to the hidden layer, which will be used as training data for the ANN. The weighted value W1, W2 and W3….Wi is passed on to the neuron, where it is modified by the threshold function, such as sigmoid function. The output layer receives all the responses from hidden layer, and exports a corresponding output.

Input 1

Input 2

Input j

Input n

X1

X2

Xj

Xn

Outputs

Transfer function

Weights

bj

F(sj)

Sj

yj

**Figure 7**: Basic structure of an artificial neuron

The output of any neuron is given by the following equation:

 (2)

where n is the number of inputs, xj is the value received from the previous neuron, wij is the weight between i and j neurons and bj is the bias of the neuron.

The output of the neuron is given by:

 (3)

where f is the transfer function.

Training of the network was performed using Levenberg-Marquardt (LM) backpropagation algorithm. This algorithm is specifically designed to minimize sum-of-square error functions of the form.

The principal steps in the learning process are explained by the following algorithm:

**Step 1:** Select the number of layers, number of neurons, number of iterations, tolerance of the mean square error, and initialise all the weights and bias functions.

**Step 2.** Present the normalised input- desired output pattern sets to the neural network. The equation for updating weights and bias of each node of the neural is expressed by:

 (4)

Based on LM learning algorithm, the weight change can be assumed by:

 (5)

where z is the learning step,  is the ± incremental change in the weight, J is Jacobean matrix that contains first derivatives of the network errors with respect to the weights and biases, μ is the adaptive training parameter, I is the identity matrix**,** e is the vector of network errors and α is the momentum term.

**Step 3:** Calculate the mean square error (MSE) of all outputs as:

 (6)

where n is the number of sets that include input and output data, aj are the output based on the input values while tj are the corresponding predicted output values.

**Step 4:** Calculate total mean error. If error is less than the permissible limit, then stop else go to step 2.

In addition, the absolute fraction of variance (R2) is defined as follows:

 (7)

Figure 8 illustrates the ANN structure used in this study. It consists of three input layers (foam thickness (e), length between supports (L) and punch radius (Rp)), one hidden layer and one output (Springback). The input and output data required for training the neural network is the numerical results.

Springback

Foam thickness (e)

Length between supports (L)

Punch radius (Rp)

Input layer

Hidden layer

Output layer

**Figure 8**: Basic structure of an artificial neuron

As mentioned above, the results obtained from FEA simulations were used to train the neural networks. Several networks were investigated considering various scenarios with different numbers of hidden layers, as well as different quantity of neurons inside each hidden layer. All the possible ANN cases were accessed through a MATLAB script, and eventually the one with the lowest generalization error was selected as the representative.

In this study, the number of neurons in the hidden layer is changed and the Mean Square Error (MSE) is evaluated (Table 4). Once the MSE of the raining data reached the target value, the training is terminated and the weights and biases are automatically saved by the program. After several trials, the number of neurons which results least MSE is selected for hidden layers and is 12. The designed architecture becomes 3-12-1.

**Table 4**: Effect of the number of neurons in the hidden layer on the MSE and R2

|  |  |  |
| --- | --- | --- |
| Number of neurons | MSE | R2 |
| 8 | 0.0011545 | 0,95128 |
| 9 | 0,0058307 | 0,97964 |
| 10 | 0,00029671 | 0,98257 |
| 11 | 0,00013571 | 0,98466 |
| 12 | 3,67E-06 | 0,99286 |

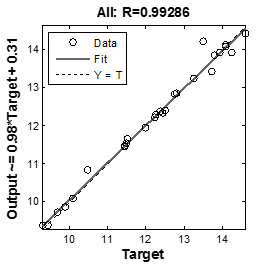
* 1. **Analysis Results**

The prediction of the model has been confirmed with the numerical results for the aim of validating the neural network approach. Table 5 gives the numerical prediction and the corresponding neural network predictions of springback. It can be inferred that the maximum error is 11 %. This table shows that results obtained by FEM and the values predicted by ANN were very close to each other. Also, this table shows that the springback amount decreases with the increasing of the foam core thickness. However, the springback increases with the increasing of the punch radius and length between supports.

Table 5: Comparison of numerical and Predicted Values of Springback

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Test N°** | **e (mm)** | **L (mm)** | **Rp (mm)** | **∆Yp FEM (mm)** | **∆Yp ANN (mm)** | **Error (%)** |
| 1 | 20 | 200 | 82 | 11,45 | 11,45 | -0,02 |
| 2 | 20 | 200 | 102 | 11,46 | 11,25 | 1,83 |
| 3 | 20 | 200 | 115 | 11,52 | 11,07 | 3,89 |
| 4 | 20 | 250 | 82 | 12,76 | 13,01 | -1,99 |
| 5 | 20 | 250 | 102 | 12,50 | 13,04 | -4,31 |
| 6 | 20 | 250 | 115 | 12,37 | 12,34 | 0,23 |
| 7 | 20 | 300 | 82 | 14,09 | 13,94 | 1,10 |
| 8 | 20 | 300 | 102 | 13,92 | 13,86 | 0,45 |
| 9 | 20 | 300 | 115 | 13,73 | 13,42 | 2,28 |
| 10 | 40 | 200 | 82 | 10,49 | 10,77 | -2,69 |
| 11 | 40 | 200 | 102 | 10,11 | 10,10 | 0,13 |
| 12 | 40 | 200 | 115 | 9,89 | 10,24 | -3,56 |
| 13 | 40 | 250 | 82 | 12,25 | 12,86 | -5,00 |
| 14 | 40 | 250 | 102 | 11,99 | 12,50 | -4,21 |
| 15 | 40 | 250 | 115 | 11,50 | 11,38 | 1,03 |
| 16 | 40 | 300 | 82 | 14,09 | 13,78 | 2,19 |
| 17 | 40 | 300 | 102 | 14,25 | 14,03 | 1,57 |
| 18 | 40 | 300 | 115 | 14,59 | 13,71 | 6,00 |
| 19 | 60 | 200 | 82 | 9,30 | 10,35 | -11,26 |
| 20 | 60 | 200 | 102 | 9,45 | 9,87 | -4,45 |
| 21 | 60 | 200 | 115 | 9,70 | 10,17 | -4,83 |
| 22 | 60 | 250 | 82 | 12,24 | 11,35 | 7,27 |
| 23 | 60 | 250 | 102 | 12,43 | 11,29 | 9,19 |
| 24 | 60 | 250 | 115 | 12,79 | 12,28 | 4,00 |
| 25 | 60 | 300 | 82 | 13,25 | 13,61 | -2,70 |
| 26 | 60 | 300 | 102 | 13,50 | 14,10 | -4,45 |
| 27 | 60 | 300 | 115 | 13,79 | 14,11 | -2,32 |

Another way to present this comparison between the two models is illustrated by figure 10. A linear regression between all the values of the springback shows that all the points are dispersed around a line with a slope close to 1. Therefore, the regression coefficient is equal to 0.99286. Consequently, as can be noticed, a good agreement between the target and predicted output values has been accomplished.



**Figure 9**: Neural network predicted output results vs. FEA simulation target values regression.

Table 6 gives the experimental results and the ANN values of springback. It can be inferred that the maximum error is 17.47 %, which is within the acceptable range.

**Table 6**: Comparison of ANN and experimental results of springback.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Test N°** | **e (mm)** | **L (mm)** | **Rp (mm)** | **∆Yp (mm) ANN** | **∆Yp (mm) EXP** | **Error (%)** |
| 1 | 40 | 200 | 82 | 10.49 | 10,77 | 10,25 |
| 2 | 40 | 250 | 82 | 12.25 | 12,86 | 14,26 |
| 3 | 40 | 300 | 82 | 14.09 | 13,78 | 13,87 |
| 4 | 40 | 300 | 102 | 14.25 | 14,03 | 17,47 |
| 5 | 60 | 300 | 82 | 13,25 | 13,61 | 2,789 |

# Conclusion

In this paper, experiments and numerical simulations of air bending process were studied for sandwich panel made of steel /polyurethane PUR/ steel. The comparison of the numerical simulation with experimental results for load–displacement process shows a good agreement which validate the numerical analysis. In order to predict springback, finite element analysis and artificial neural network approaches were used. Predicted springback obtained by numerical simulations was been used as an input in the artificial neural network methodology. The ANN model was based on a multilayer feed forward topology and trained with LM back propagation algorithm with 12 neurons. A mean squared error (MSE) and a fraction of variance (R2) equal to 3,67E-06 and 0.99286, respectively, were achieved. The results showed strong evidence good agreements between the springback predictions obtained from ANN technique and those obtained from the FEM. Moreover, the ANN approach was being identified as highly accurate and robust prediction model. The ANN method, judged very fast in computing times. It was exploited for modeling as well as for optimization.

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