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SPRINGBACK ANALYSIS OF STRECH FORMING PROCESS USING NEURAL NETWORK

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ABSTRACT

In this study, artificial neural network has been employed to analyse springback in stretch forming process. The process variables are stretch and punch displacement. Maximum equivalent strain criteria is adopted to obtain critical punch movement. Data has been generated using finite element simulation considering 16 cases. Successfully trained network has been validated with the newer problems.

Key words: *Stretch Forming, Springback, Finite Element and Neural Network*

1. Introduction

Springback is an important factor in the design of sheet metal forming process. Springback is quite high in sheet when sheet thickness is less and forming radius is very high. The three methods currently used for controlling springback are overbending, bottoming and stretch forming. Stretch forming is the process of forming by the application of primarily tensile forces in such a way as to stretch the material over a tool or form block. Stretch forming consists of stretching the blank so that all of the metal material crosses past the elastic limit, completely eliminating springback (Dieter,1988). Stretch forming is used mostly in aircraft industry to produce parts of large radius of curvature, frequently with double curvature. Springback analysis is generally carried out using experimental and numerical techniques like finite element method. But these approaches suffer from two major problems – high expenditure and expertise. In recent years, artificial neural networks have been successfully applied in metal forming problems due to its simplicity and effectiveness. Some of the important and relatively latest literature on neural network application in metal forming are as follows:

Rao and Prasad (1995) investigated the feasibility of utilizing a neural network to extract the complex relationships involved in hot-deformation process modelling. Kim et. al. (1997) proposed a new technique to determine the initial billet geometry for the forged products using a functional approximation in neural networks. Ko et. al. (1998) employed neural networks for preform design in multi-stage metal forming processes considering workability limited by ductile fracture. Gunasekera et. al. (1998) developed a neural network model, based on the backpropagation paradigm, for the flat rolling process. Ko et. al. (1999) implemented artificial neural network and Taguchi method for minimizing objective functions relevant to the forming process. Kim and Kim (2000) used a three-layer neural network to find the initial billet size for axisymmetric rib-web product and to design the die geometry for cylindrical pulley. Cheng and Lin (2000) used three supervised neural network to estimate bending angles formed by a laser. Wang et. al. (2000) introduced a model based on an artificial neural network to reveal the critical geometrical criteria for wrinkling. Manninen et. al. (2002) discussed the dry turning of catreated steels with both uncoated and TiN-coated tools, and showed formation of a protective layer on the rake face may improve the wear life of tools nearly 30-fold. Garc´ıa (2005) designed an integrated automatic control to avoid production breakdowns and to improve the reliability of the stamping process. Zhao and Wang (2005) presented feed-forward neural network model, which was established to realize real-time identification of material properties and friction coefficient for deep drawing of an axisymmetric work piece. Xiong and Withers (2005) examined the efficiency and capability of Dynet, a recurrent neural network model for the prediction of the damage evolution during hot non-uniform, non-isothermal forging on the basis of a limited number of damage snapshots during the process. Downes and Hartley (2006) developed a technique using an artificial neural network to assist in the design of roll-forming tools. Chamekh et al. (2006) described an approach, based on artificial neural networks, to identify the material parameters of a stainless steel material. Kumar et al. (2007) applied a hybrid neural

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network model known as Recurrent Self-Organizing Neural Network Model to predict the flow stress for carbon steels. Belfiore et al. (2007) proposed a neural network model for prediction of surface damage. Wenjuan et al. (2007) proposed a technique based on artificial neural network and genetic algorithm to solve the problem of springback.

In this study artificial neural network has been used to analyse springback in stretch forming process. Extensive finite element analyses considering 16 cases are carried out to generate the data set. Using these data a back propagation neural network has been trained and successfully trained network is used for springback prediction to the newer problem. It is observed that neural network predictions for new problems are quite close to the actual FEM counterpart.

2. Artificial neutral network

Artificial neural network attempts to imitate the learning activities of the brain. The human brain is composed of approximately 10^{11} neurons (nerve cells) of different types. In a typical neuron, we can find the nucleus, where the connection with other neurons is made through a network of fibers called dendrites. Extending out from the nucleus is the axon, which transmit, by means of complex chemical process, electric potentials to the neurons with which the axon is connected to (Fig.1.). When the signals received by the neuron equal or surpass their threshold, it "triggers" sending the axon an electric signal of constant level and duration. In this way the message is transferred from one neuron to other.

In an artificial neural network (ANN), the artificial neuron or the processing unit may have several input path corresponding to the dendrites. The units combine usually, by a simple summation, the weighted values is of these paths (Fig.2). The weighed value is passed to the neuron, where it is modified by the threshold function such as sigmoid function (Fig.3). The modified value is directly presented to the next neuron.

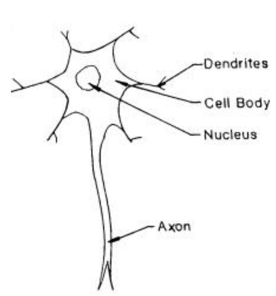

Fig. 1 A Typical Biological Neuron

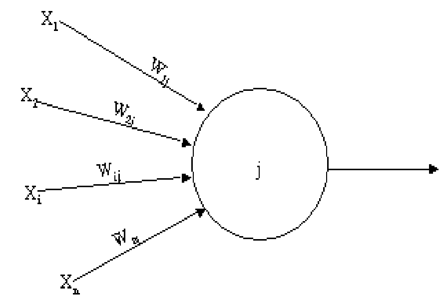

Fig. 2 A single Processing Unit

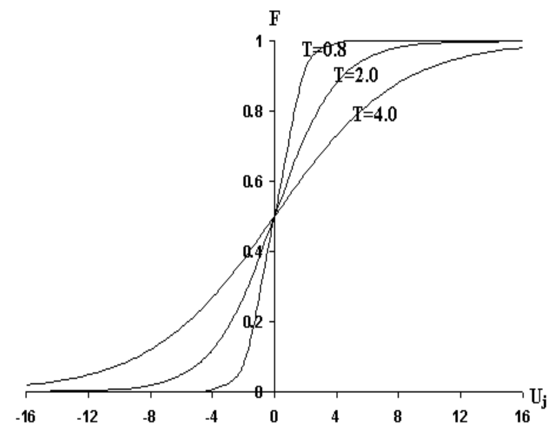

Fig. 3 The Sigmoid Function

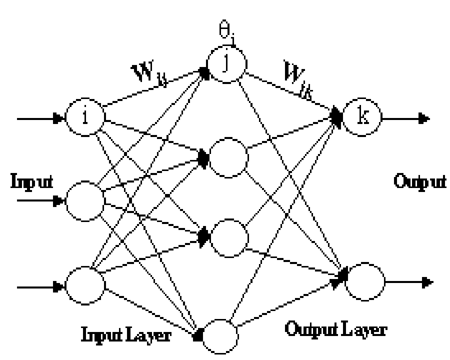

Fig. 4 Neural Network

In (Fig.4) a 3-4-2 feed forward back propagation artificial neural network is shown. The connections between various neurons are strengthened or weakened according to the experiences obtained during the training. The algorithm for training the back propagation neural network can be explained in the following steps-

Step 1 – Select the number of hidden layers, number of iterations, and tolerance of the mean square error and initialize the weights and bias functions.

Step 2 – Present the normalized input –output pattern sets to the network. At each node of the network except the nodes on input layer, calculate the weighted sum of the inputs, add bias and apply sigmoid function.
Step 3 – Calculate total mean error. If error is less than permissible limit, the training process is stopped. Otherwise,
Step 4 – Change the weights and bias values based on generalized delta rule and repeat step 2.

The mathematical formulation of training the network can be found in Hertz and Krogh (1991).

3. Geometrical and Material Parameters

Stretch bending is performed on a rectangular sheet of 200 mm length and 60 mm width. Punch has a cylindrical profile with radius of 186 mm. The sector angle of the cylindrical segment is 52.8 degree. At the punch corner a billet of radius 2 mm is provided. Geometrical parameters of the set up are shown in Fig.5.

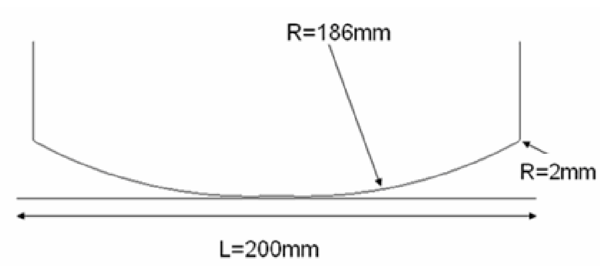

Fig. 5 Sheet and Punch Dimension

Four sheet thicknesses viz.1,1.5,2 and 2.5 mm are considered for stretch forming. Sheet is considered to be made of steel having elasto-plastic material properties. Following material properties are considered:
Young's modulus (E) =2.1 x 10^5 MPa
Poison ratio (υ) =0.3
Yield strength = 400 MPa
Elasto-plastic flow properties are accounted as per the data given in Table 1.

Table 1: Flow Stress Strain Data

Yield Strength (MPa)	Plastic Strain
400	0.0
420	0.02
520	0.2
600	0.5

Four values of the stretching viz 1, 1.5, 2 and 2.5 mm are considered. Considering the variations in sheet thickness and stretch, 16 cases are framed.

4. Finite Element Analysis

Finite element (FE) modeling of stretch forming set up is carried out using four nodded shell elements using ABAQUS/CAE software. Taking advantage of symmetry, only half part is used for FE meshing. The FE model is shown in Fig.6.

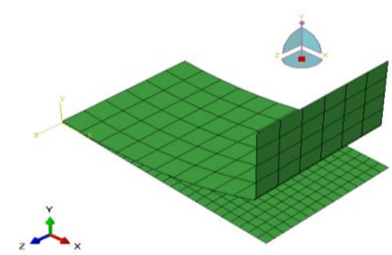

Fig. 6 FE Model

There are 375 elements and 416 nodes in the model. Punch is modeled as deformable bodies. For symmetric boundary condition nodes on left hand side are restricted in X direction. Stretching is carried out by applying displacement boundary condition to the nodes on right hand side. Bending is attempted after the stretching. For this punch is given displacement to achieve constant plastic strain value of 0.035 (fracture strain) for each of the 16 cases. Interaction between the sheet and punch are accounted using contact. Coulomb friction coefficient value of 0.1 is considered between punch and sheet surface for all the cases. Loadings, in terms of displacement boundary condition, are applied in three steps:
Step 1 – It relates to stretching process of duration 1 sec.
Step 2 – It relates to punch displacement in y direction. Its duration is 2 sec.
Step 3 – It is the release of punch in time of 0.2 sec.
The displacement time plot showing these steps is shown in Fig.7

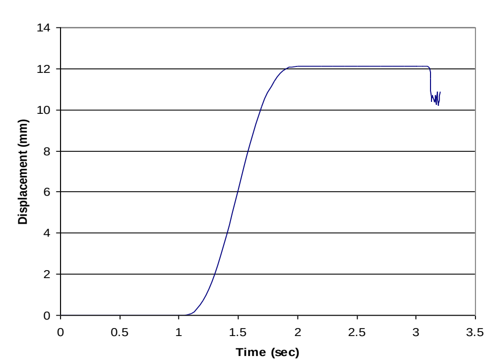

Fig. 7 Displacement Vs Time Plot

Finite element analyses have been carried out using ABAQUS/Explicit software (Ref.17). For simulation, time scale factor in each step is kept as 1. Punch displacement for each case to achieve the strain of 0.0035 is given in Table 2. Geometrical non-linearity has also been accounted. FE simulation results are collected in terms of springback, residual stress and reaction force for each case and given in Table 2.

Table 2: Springback in Stretch Forming

S. No	Sheet Thickness (mm)	Stretch (mm)	Punch Displacement (mm)	Springback (mm)	Residual stress (MPa)	Reaction Force (N)
1	1	1	16.423	1.314	265.1	5460
2	1	1.5	15.315	1.443	203.2	5194
3	1	2	14.02	1.55	276.6	4571
4	1	2.5	11.618	1.84	176.3	3621
5	1.5	1	17.02	1.159	145.7	9112
6	1.5	1.5	15.82	1.349	229.8	8177
7	1.5	2	14.019	1.56	263.3	6901
8	1.5	2.5	12.108	1.612	185.8	5750
9	2	1	16.705	1.169	237.3	11262
10	2	1.5	15.604	1.393	197.0	10715
11	2	2	14.102	1.588	263.5	9284
12	2	2.5	11.314	1.899	301.9	7062
13	2.5	1	16.915	1.167	191.6	15020
14	2.5	1.5	16.015	1.306	216.6	13890
15	2.5	2	14.908	1.477	299.1	12500
16	2.5	2.5	12.103	1.644	263.0	9618

5. Application of Neural Network

Alternate methods of analyzing stretch forming process using analytical techniques and experimental study are quite time consuming. Finite element analysis of springback, although quite effective, requires costly software and expertise. Application of ANN along with FE simulation can give such a "intelligent" data base which can be readily available for instant use and evades dependencies on expensive FE package. A simple "put the value and get the estimate" approach using ANN will make the designer's first hand job extremely simple. Using FE results, a neural network is trained in order to automate the analysis process. Sixteen data sets mentioned above are used for the training of the neural network. A 2-4-1 size of back propagation neural network is used for the training of the data. Input parameters of the neural network are stretch and sheet thickness whereas output parameters are springback. Weights and bias values are taken between -0.05 to 0.05. It took 467352 epoches to converge to an error tolerance of 0.009. The neural network predictions are tested using 7 new sets of data and are given in Table 3.

Table 3: Validation of the Contour Map

S. No.	Thickness (mm)	Stretch (mm)	Springback (mm) (FEM)	Springback (mm) (Neural Network)	% Error
1	2	2.4	1.68	1.70	1.19
2	1.5	2.3	1.61	1.65	2.48
3	1.165	1.7	1.45	1.48	2.06
4	2	2.2	1.64	1.62	1.21
5	2.2	2.2	1.63	1.61	1.22
6	1.2	1.2	1.35	1.31	2.96
7	1.6	1.4	1.35	1.34	0.74

It can be observed that maximum error is 2.96 %, which is quite acceptable for first hand assessment. It can be also observed that neural network not only saves huge amount of computational time going into FE simulations but also offers an inexpensive tool as it avoids the dependencies on costly FE software and expertise to handle them.

6. Conclusion

In this study artificial neural network has been employed for the analysis of springback in stretch forming process. Neural network, trained using the FE simulation results, is used for this purpose. Neural network predictions, when compared to FE counterpart, are found to be in close match. Neural network based springback analysis is fast and economical as it doesn't require costly FE software and expertise. The proposed approach can be a very effective tool, especially at initial stage, of stretch forming process design.

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