Development an Integrated Framework for Springback Prediction in Bending

Fayiz Y. Abu Khadra, Jaber E. Abu Qudeiri*
King Abdulaziz University, Faculty of engineering-Rabigh, Mechanical Engineering Department, Rabigh 21911, Saudi Arabia
*Advanced Manufacturing Institute King Saud University - Riyadh 11421, Saudi Arabia
E-mail: dr.qudeiri@gmail.com

Abstract: Bending has significant importance in the sheet metal product industry. Moreover, the springback of sheet metal should be taken into consideration in order to produce bent sheet metal parts within acceptable tolerance limits and solve geometrical variation for control of manufacturing process. The Air bending process offers the advantage that many less tool changes are required as compared with others bending processes, however the calculation of the required punch displacement presents some problems. In this paper, several numerical simulations using finite element method were performed to obtain the teaching data required for training the neural network by means of the back–propagation algorithm. In the predictive mode different process inputs from the ones used in the previous stage were considered, for each case the springback angle and the displacement required to achieve a certain angle after springback are predicted by the learned network. Fairly accurate results were achieved for the punch displacement and for the springback angle evens so the range considered for training the network is large. The neural network can be easily implemented in experiment or in real production to determine the punch displacement to achieve a certain bend angle within a narrow range around the desired angle.

[Fayiz Y. Abu Khadra, Jaber E. Abu Qudeiri. **Development an Integrated Framework for Springback Prediction in Bending.** *Life Sci J* 2013;10(2):1654-1659]. (ISSN:1097-8135). http://www.lifesciencesite.com. 230

Keywords: Springback; finite element simulation; artificial neural network

1. Introduction

Sheet metal bending is an important manufacturing operation in many industrial processes. The elastic recovery after unloads causes the springback phenomenon in which the radius of curvature of any fiber in bending increases after bending moment is removed. Precise prediction of springback, in the design stage of the tools and selection of the sheet materials is very valuable in reducing cost of very expensive trial and error methods are which still being used. A number of analytical models based on materials properties and tool geometry is available to predict springback [1-6]. Most of the analytical models based on a lot of simplifying assumption due to the complexity of the problem and they do not provide accurate predictions. The finite element method becomes reliable to simulate the process before experimental development and die tryout are conducted [8-14]. The use of the FEM significantly improves the planning and control of the manufacturing process at the design stage before dies are manufactured and expensive production machinery is tied up for costly experimentation, one draw back of the finite element method is the relatively long time so that it can not be used in real time control of the bending process. An emerging alternative approach involves the development of control system based on artificial neural networks (ANNs). ANNs are fault tolerant and robust, are amenable to parallel implementation and are faster than conventional computing. They can be trained using a set of data to predict to a reasonable accuracy the result for new set process parameters. In recent years, many research groups have investigated the use of artificial neural networks to control sheet-forming processes. Sheet metal forming is an ideal candidate for neural network control due to the nonlinear effects caused by the interactions of the process parameters. Cho et al [15] used a neural network to predict the force in cold rolling, and DI and Thomson [16] predicted the wrinkling limit in squares metal sheets under diagonal tension Ruffini and Cao [17] proposed to use a neural network to control springback angle in a channel forming process with punch force trajectory as the sole source for identifying the process variations and adjusting the blank holding force.

The objective of this article is to develop a neural network with the help of the finite element method prediction of springback For this purpose a validated finite element model will be used to generate training sets for the artificial neural network for prediction of springback, and the displacement required to achieve a bend angle after springback taken into account the process parameters and material properties which influence the springback of metal sheet.

2. Finite Element Modeling

Figure 1 illustrates a schematic view of the air bending process. The bending operations simulated in this study were performed in 2D since the width to thickness ratio of the sheet allows plane strain conditions to be assumed. Therefore, the bending process, which includes contact of multiple rigid bodies and a deformable body, is analyzed using four-node quadratic plane strain elements. The implicit model is based on the updated Lagrange formulation, which takes into, account both material and geometrical non-linearites. In the update Lagrangian formulation the element stiffness is assembled in the current configuration of the element. The equilibrium in the Lagrangian schema, and by Hill's variation principle can be expressed in the form [18].

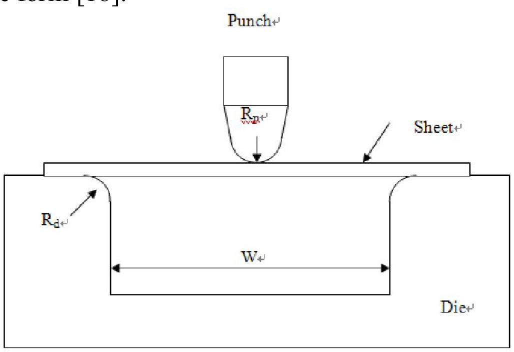

Figure1: Schematic view of the air bending process

$$\int_V \left[\left(\dot{\tau}_{ij} - 2\sigma_{ik}\dot{\varepsilon}_{ij}\right)\delta\dot{\varepsilon}_{ij} + \sigma_{ik}L_{ik}\delta L_{ij}\right]dV = \int_{S_f} \bar{t}_i \delta v_i dS, \quad (1)$$

So that an incremental elastic-plastic constitutive relation is incorporated into it which is given by:

$$\tau_{ij} = \frac{E}{1+\nu}\left[\delta_{iK}\delta_{ij} + \frac{\nu}{1-2\nu}\delta_{ij}\delta_{Kl} - \frac{3\alpha(E/1+\nu)\sigma'_{ij}\sigma'_{Kkl}}{2\bar{\sigma}^2(2/3)H' + E/(1+\upsilon)}\right]\dot{\varepsilon}_{Kl}, \quad (2)$$

Where E is the modulus of elasticity, ν the poisson's ratio, H' the strain hardening rate, α a constant equal 1 for plastic state and equal 0 for the elastic state, σ'_{ij} the deviatoric part of σ_{ij}, and $\bar{\sigma}$ the effective stress. Eq. (2) is used to model the elastoplastic behaviour of the sheet metal.

The sheet material considered as an isotropic hardening, which means that the yield surface remains the same shape and has the same origin during hardening, with only the size changing, i.e. radius of the yield surface expands, due to work hardening. The equivalent stress-equivalent plastic strain relation of the sheet is assumed to follow the form:

$$\bar{\sigma} = c(\varepsilon_0 + \bar{\varepsilon}_p)^n \quad (3)$$

The boundary condition assures full symmetry and is applied in the line of symmetry preventing any movement from those in the x-direction .The curves that define the shape of the die and the punch are interpret as rigid bodies. They are in contact with the sheet, which actually a deformable body, contact between a deformable body and a rigid body means that nodes do not penetrates the rigid body. The punch motion is controlled using a time versus displacement table.

The full Newton-Raphson method was chosen for the solution of the nonlinear finite element equations. The Newton-Raphson iteration method operates as follows [18],

$$\Delta u^{i+1} = \Delta u^i + K_t^{-1}(F^i - I^i), \quad (4)$$

The Newton-Raphson Method, based on an incremental step-by-step solution, assumes the equilibrium configuration of the body at a discrete time t and determines the solution for the discrete time t+Δt, where Δt is the time increment. The method has quadratic convergences properties and the stiffness matrix is reassembled at each iteration. This means that in subsequent iteration the relative error degreases quadratically. The correct choices of Δt is fundamental to obtain a quick iterative convergence. Moreover, such a choice strongly influence the validity of the contact algorithmic particular, to obtain effective solutions often requires very small values of the time increment. Since at each step the stiffness matrix must be assembled and inverted with the above iterative procedure, the CPU times required to complete the simulation of the process are typically very high.

In order to take into account the friction between the sheet and the tools, Coulomb friction model is implemented. The coulomb model is [19]:

$$\sigma_{fr} \leq -\mu\sigma_n t, \quad (8)$$

Where σ_n are the normal stress, σ_{fr} the tangential friction stress, and μ the friction coefficient. The tangential vector t in the direction of the relative velocity

$$t = \frac{v_r}{|v_r|}, \quad (9)$$

When the implicit finite element analysis is used in combination with an elastic plastic material model, it allows simulation of springback upon the removal of all contact loads in the fully loaded state. The release option is used to enable releasing of the deformable body's nodes, which have been in contact with the rigid bodies, i.e. removing the rigid surface, and evaluating mechanical springback.

3. Artificial neural networks

Visual inspection of a given set of plotted data may suggest an obvious nonlinear relation ship, but the exact relation may not be apparent. A least-squares model determines the coefficient within an algebraic expression, but one must have some idea of the desired form of this algebraic expression, before seeking the coefficients values. An automated approach that addresses this need is the use of artificial neural networks since they are easy to use and widely applicable as approximates for problems with highly nonlinear and complex data. ANN models can identify and learn correlated patterns between sets of input data and corresponding target values. After training phase, such nets can be used to predict the outcomes from new input data. These features make neural nets well suited for solving problems in the area of preprimary design, where such approximates can be used to reduce the computational time. The structure of the neural network is defined by several neurons, arranged in different layers (input, hidden and output) as shown in **figure 2**, the interconnection between the neurons, the rules determining whether or not a neurons executes a transfer function, and the rules governing changes in the interconnecting weights known as training laws.

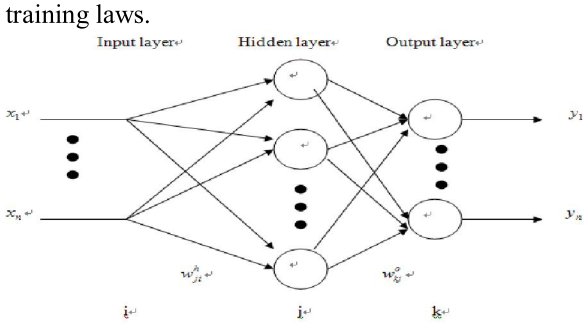

Figure 2: A three-layered neural network

Figure 3 shows the process of training the ANN. The output z_i produced by the jth neuron in the hidden layer is given by the following relationship[20]:

$$z_i = f_j^h\left(\sum_{i=1}^{n} w_{ij}^h x_i\right) \tag{10}$$

Where is f_j^h the activation function, n is the number of the elements in the hidden layer $W_{i,j}$ is the weight associated with the connection between the neurons i in the input layer and the neuron j in the hidden layer whose output is z_i. The output from the sth neuron of the output layer is given by:

$$y_s = f_s^o\left(\sum_{j=1}^{l} w_{sj}^o z_j\right) \tag{11}$$

The weights of the output are updated using the following relationship:

$$w_{sj}^o(k+1) = w_{sj}^o(k) + \eta\delta_s(k)z_j(k) \tag{12}$$

And the weights for the hidden layer neurons are updated using the following relation:

$$w_{ij}^h(k+1) = w_{ij}^h(k) + \eta\left(\sum_{o=1}^{m} \delta_p^k(k) w_{pj}^o(k)\right) f_j^{h'}(v_j(k)) x_{di} \tag{13}$$

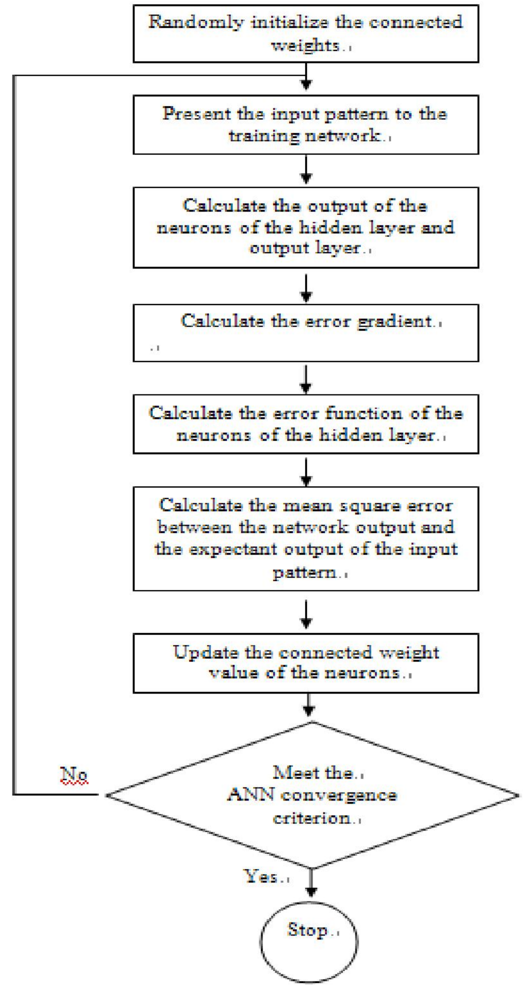

Figure 3: Flow chart for the learning algorithm of the neural network

The above update equations are referred to in the literature as the back propagation algorithm. In this algorithms the output errors are propagated back from the output layer to the hidden layer, and are used in the update equation for the hidden layer weights. Back-propagation iteration is completed when equations 12 and 13 are applied to all neurons of the network; then, the process restarts with a new/output pattern presentation. The system adjusts the weights of the internal connections to minimize errors between the network output and target output. The knowledge is represented and stored by weights of the connections between the neurons. The training of the neural network involves adjusting the weights of connections such that the output generated by the network for the given input is as close to output as possible. This is achieved by minimizing the learning error, defined by the mean square error (MSE):

$$MSE = \frac{1}{QN_0}\sum_{m=1}^{Q}\sum_{n=1}^{N_0}\left[d_n(m) - y_n(m)\right]^2 \tag{14}$$

After the neural network is satisfactorily trained and tested, it is able to generalize rules and will be able to respond to unseen input data to predict required output, within the domain covered by the training examples.

3.2 Development of the Neural Network algorithm

A fundamental step in utilization of ANNs is the achievement of input /output data necessary for the training stage. They can be obtained from actual bending experimentation or from FEM simulations. In the later case, elastic springback can be successfully predicted, whilst eliminating the need for expensive experimentation. In air bending, it is known that springback varies with material properties and process parameters. The following factors were identified to have significant effects on springback; ratio of yield strength to young's modulus, the ultimate tensile stress, the sheet thickness, the punch radius, the die radius, the die width, the friction coefficient, and the bend angle after springback. The punch displacement required to achieve a desired bend angle, and the mount of springback are the two outputs of the ANN. Using the finite element model described in previous section. A series of numerical simulation have been carried out to generate training set for the neural network using different sheet thickness in the range of (1-6 mm), punch and die radii between (4-20 mm), die width (40-100 mm) friction coefficient in the range (0-0.5) and more than 40 different materials.

A three layer neural network was developed with a sigmoid activation function between the layers which is given by:

$$f(v) = \frac{1}{1+e^{-v}} \qquad (15)$$

The determination of the optimal number of hidden neurons is crucial for the predictive capabilities of the network with too few hidden layer neurons, the input–output relationship would not be learned adequately leading to a higher mean square error. With too many hidden layer neurons, the neural network would be oversensitive and not adapt well to new inputs not seen during training, leading to high mean square error. Using a trial and error process the training error is minimized when seven neurons in the hidden layer are used. With this number of the hidden layer neurons the structure of the neural network is determined to be eight inputs, seven hidden layer neurons, and two outputs with a learning rate of 0.9.

4. Results and discussion

Ones the neural network structure was well established and trained the predictive performance of the neural network is tested. The performance of the developed ANN measured by MSE error vs. the training number (epochs) is presented in **Figure 4**. It can be shown that after $2x10^5$ training cycles, the curve stabilizes which means that the ANN has been sufficiently trained. Results of the network training are presented in **Figure 5** and **Figure 6**, which shows a perfect match between the target output, and the ANN output for both the springback angle and the displacement required to achieve a certain bend angle.

Beside the evaluation of the performance of the model, it is also interesting to consider the relative importance of each input variable in estimating the outputs of the network. Table 1 displays the contribution factors associated with each of the input variables. The contribution factor of the neural network is the sum of the absolute values of the connection weights leading from each neuron, which represent the explanatory variable. By examining these factors, some useful information with respect to the relations between different factors and the springback angle and the displacement to achieve a required bend angle after springback can be obtained. From **table 1** it is clear that the die width, the sheet thickness, the yield strength to young's modulus ratio and the bend angle after springback are the most significant factors, which affect springback and the displacement required to achieve a certain bend angle where the other inputs have comparatively little effect on the two outputs of the neural network.

An easy and fast parametric study can be performed using the developed neural network as illustrated in the **figures 7, 8,9** where the effect of three process parameters, which have comparatively large effect on springback, are studied. In figure 7 the displacement required to achieve a certain bend angle increases with increasing die width. Figure 8 shows that with increasing punch radius the displacement to achieve a desired bend angle decreases. Figure 9 shows that with increasing die radius the displacement required to achieve a required bend angle increases.

Table 1: Contribution factors of the variables in the neural network model

Input	Contribution factors
Yield strength to young's modulus ratio	0.1658
Ultimate tensile strength	0.0813
Sheet thickness	0.184
Punch radius	0.0611
Die radius	0.1007
Die width	0.1934
Friction coefficient	0.0932
Desired bend angle	0.1203

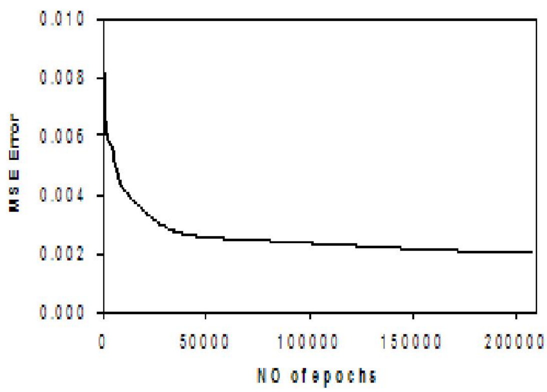

Figure 4: MSE error vs. number of epochs

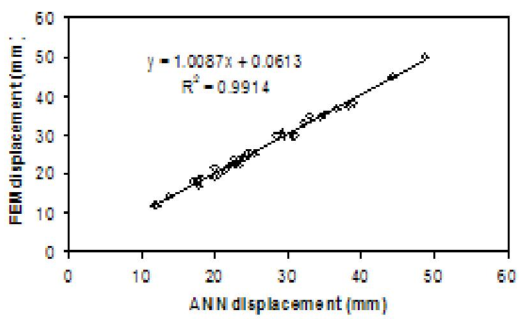

Figure 5: Comparison between the FEM displacement and the ANN displacement

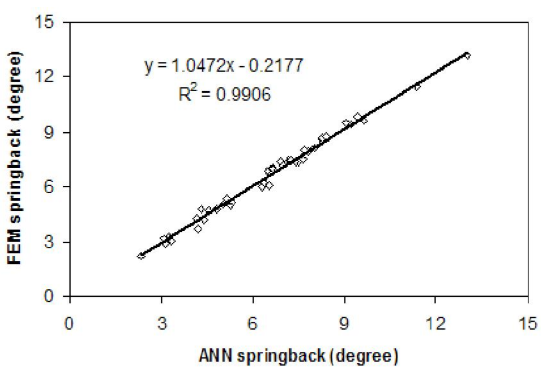

Figure 6: Comparison between the FEM springback angle and the ANN springback angle

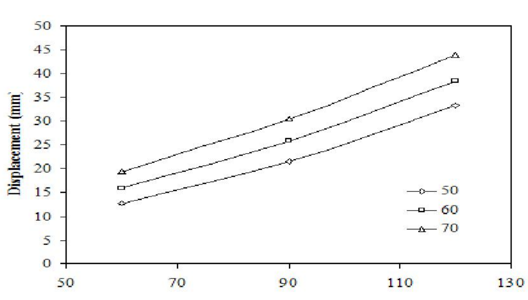

Figure 7: Bending angle and the required punch displacement for different die widths

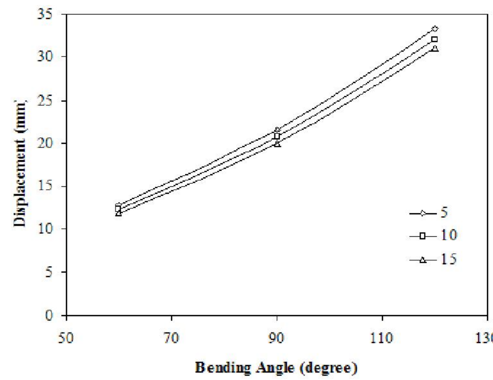

Figure 8: Bending angle and the required punch displacement for different punch radii

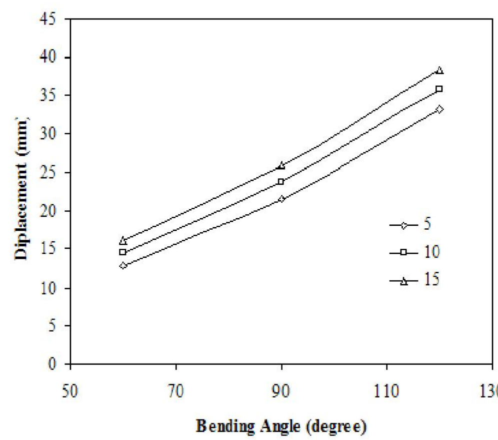

Figure 9:Bending angle and the required punch displacement for different die radii

4. CONCLUSIONS

In this study a finite element model and a developed neural network algorithm were used to predict springback and the displacement required to achieve a desired bend angle. Effect of material properties and tool geometry on springback has been investigated. It has been found that the displacement required to achieve a certain bend angle increases with: increasing die radius, die opening width, and decreasing punch radius. From the study it is clear that springback in air bending can be well controlled by over bending the sheet metal to correct amount. By this model, deviation between the predicted bend angles on unload and the desired bend angles measured is within a narrow range around the desired bend angle. A neural network was chosen due to its ability to handle the highly non-linear coupled effects that are found in sheet metal bending process when variations in the material and process parameters occur. While the work was conducted using simulations, the methodology developed could be easily extended to an actual forming processes or experiments. Though a neural network system requires more front work producing a sufficient number of examples to train the network, the benefits for controlling and studying springback are undeniable.

***Corresponding author:**
Jaber E. Abu Qudeiri*,Advanced Manufacturing Institute King Saud University, Riyadh 11421, Saudi Arabia, E-mail: dr.qudeiri@gmail.com

REFERENCES

[1] Johnson W and Yu T. Springback after the biaxial elastic-plastic pure bending of rectangular plate I. International Journal of Mechanical Sciences 1981;23:619–30.
[2] Yu T and Johnson W. Influence of axial force on the elastic–plastic bending and springback of a beam. Journal of Mechanical Working Technology 1982;6:5–21.
[3] Chu C. Elastic–plastic springback of sheet metals subjected to complex plane strain bending histories. International Journal of Solids Structures 1986;22: 071–81.
[4] El-Megharbel A, El-Domiaty A, and Shaker M. Springback and residual stresses after stretch bending of working sheet metal. Journal of Materials Processing Technology 1990;24:191–200.
[5] Asnafi N. Springback and fracture in V-die air bending of thick stainless steel sheets. Materials and design 2000;21: 217-236.
[6] Wang C, Kinzel G, Altan T. Mathematical modeling of plane-strain bending of sheet and plate. Journal of Materials Processing Technology 1993;39:273–304.
[7] Zhang Z, and Lee D. Development of a new model for plane strain bending and springback analysis. Journal of Material Engineering and Performance 1995;4:291–300.
[8] Pourboghrat F, and Chu E. Springback in plane strain stretch-draw sheet forming. International Journal of Mechanical Sciences 1995;36:327–41.
[9] Pourboghrat F, Chung K, and Richmond O. A hybrid membrane/shell method for rapid estimation of springback in anisotropic sheet metals. ASME Journal of Applied Mechanics 1998;65:671–84.
[10] Nagtegaal J, and Taylor L. Comparison of implicit and explicit finite element methods for analysis of sheet forming problems, in: FE-Simulation of 3-D Sheet Metal forming Processes in Automotive Industry, VDI, Berichte, vol. 894, 1991, pp. 705-725.
[11] Lia K, Carden W, and Wagoner R. Simulation of springback. International Journal of Mechanical Sciences 2002; 44:103–122.
[12] Papeleux L, and Jean-Philippe Ponthot J. Finite element simulation of springback in sheet metal forming. Journal of Materials Processing Technology 2002:125–126:785–791.
[13] Gantar G, Pepelnjak T, and Kuzman K. Optimization of sheet metal forming processes by the use of numerical simulations. Journal of Materials Processing Technology 2002;130–131: 54–59.
[14] Hamouda A.M.S., Abu Khadra F, Hamadan M.M., Imhemed R.M., and MahadiE. Springback in v-bending: a finite element approach. Int. J. Materials and Product Technology 2004;21:124-136.
[15] Cho S, Cho Y, and Yoon S. Reliable Roll Force Prediction in Cold Mill Using Multiple Neural Networks1997. IEEE Transactions on Neural Networks; 8: 874–82.
[16] Di S and Thomson P F. Neural Network Approach for Prediction of Wrinkling Limit in Square Metal Sheet under Diagonal Tension. Journal of Testing and Evaluation 1997; 25: 74–81.
[17] Ruffini R and Cao J. Using Neural Network for Springback Minimization in a Channel Forming Process. Developments in Sheet Metal Stamping 1998: SAE Paper 98M-154,SP-1322: 77-85.
[18] Hill R. The Mathematical Theory of Plasticity. London: Oxford university press, 1950.
[19] MARC. Theory and User Information. MSC.Marc 2001.
[20] Haykin S. Neural Networks—A Comprehensive Foundation. New York. Macmillan, 1994.

5/25/2013