Neural Network Prediction of Nonlinear Elastic Unloading for High Strength Steel

***M. R. Jamli[1,2], A. K. Ariffin[1], and D. A. Wahab[1]**

[1]Department of Mechanical and Materials Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia 43600, Bangi, Selangor, Malaysia
2Department of Manufacturing Process, Faculty of Manufacturing Engineering, Universiti Teknikal Malaysia Melaka,Hang Tuah Jaya, 76100, Durian Tunggal, Melaka, Malaysia

*Corresponding author: ridzuanjamli@utem.edu.my

Abstract

In achieving accurate results, current nonlinear elastic recovery applications of finite element (FE) analysis have become more complicated for sheet metal springback prediction. In this paper, an artificial neural network (ANN) was used to mimic the nonlinear elastic recovery and provides a generalized solution in the FE analysis. The nonlinear elastic recovery was processed through back-propagation networks. This approach is able to perform pattern recognition and create direct mapping of the elastically-driven change after plastic deformation. The FE program for nonlinear elastic recovery experiment was carried out with the integration of ANN. The results obtained at the end of the FE analyses were closed to the measured data.

Keywords: Finite element, neural network, non-linear recovery, springback prediction

Introduction

One of the problems in the sheet metal forming process is the springback phenomenon. This phenomenon occurs due to the elastic recovery, which is influenced by the elastic properties and the plastic flow of the sheet metal material. Although the elastic recovery contributes only small strain if compared to the plastic strain, the final shape of a sheet metal forming product is significantly affected due to the accumulative small strain in corner radii and sidewall of curved surface (Kim et al. 2013). Most of the current finite element (FE) method practices still utilize the classic elastoplasticity theory, which assumes that the unloading modulus after plastic deformation is parallel to the initial Young's modulus. However, several investigations have shown that the unloading modulus is influenced by accumulated plastic strain (Cleveland and Ghosh 2002; Li et al. 2002; Yoshida et al. 2002; Andar et al. 2010). Furthermore, several investigations have found that the unloading stress-strain curve actually shows nonlinear elastic recovery (Cleveland and Ghosh 2002; Cáceres et al. 2003; Andar et al. 2010; Chatti and Hermi 2011; Sun and Wagoner 2011). The development of an additional surface in the yield surface (Eggertsen and Mattiasson 2010) and the transition of the elastic to the plastic model (Quasi-Plastic-Elastic model) (Sun and Wagoner 2011) have been proposed for the description of nonlinear elastic recovery in constitutive modeling. However, due to the complexity of developing the nonlinear recovery model, the variable elastic modulus achieves a relatively wider range of application in springback predictions (Chatti and Hermi 2011; Zhu et al. 2012).

The applications of an artificial neural network (ANN) as the parameters identification tool for the FE springback analysis provide solution without solving the nonlinearity problems(Aguir et al. 2008; Kazan et al. 2009; Veera Babu et al. 2010;

Aguir et al. 2011). Thus in this paper, ANN was used to mimic the nonlinear elastic recovery and provides a generalized solution in the FE analysis. The implementation of ANN in the constitutive model of the FE software requires an additional technique to achieve better generalization. This is to ensure that the developed ANN model is utilizable in a wide range of the FE springback analysis.

Methodology

The application of ANN is split into the curve regeneration and interpolation coefficient parts. A new curve is generated from the raw experimental data and the output is used as an input to the interpolation coefficient part. This procedure is discussed further in the next subsection.

3.1 The Database and its Regeneration

This study utilized the experimental data that have been published by (Sun and Wagoner 2011). The published data were chosen based on their comprehensiveness in providing information from the identification of material parameters until the measurement of springback. Figure 1 shows the tensile test result for a DP 980 steel sheet with intermediate unloading cycles. The hysteresis loops are noticeable significantly as the flow stresses increase prior to unloading. Figure 2a shows the magnified view of the fourth cycle from Figure 1. A chord modulus (E_{av}) of 145GPa and an initial Young's modulus (E_0) of 208GPa are shown for comparison. It is shown that the current elastic modulus (E_c) varied at different normalized stress points(σ_1/σ_0). Figure 2b shows the regeneration of the unloading curve by the first ANN, whose architecture was investigated in two cases, as shown in Table 1. The true strain and true stress are the input and the output of the network.

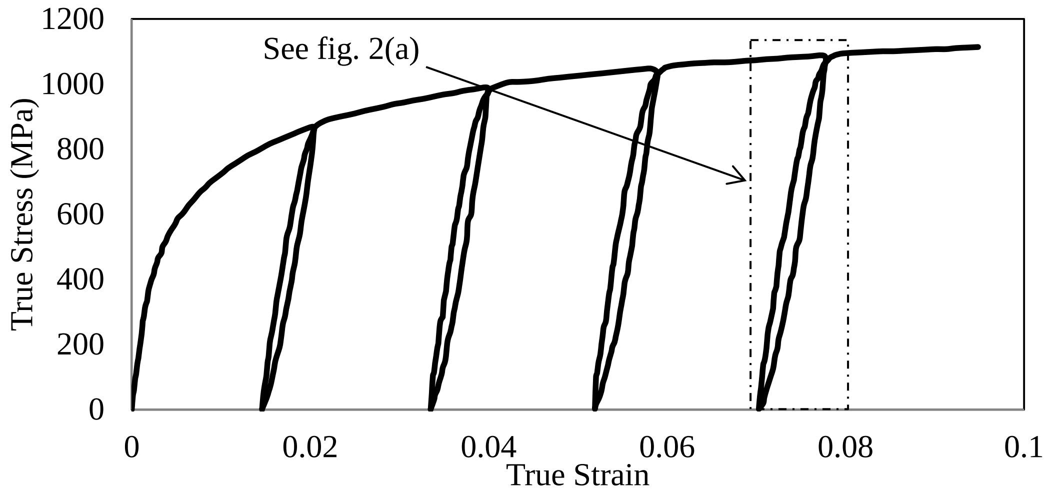

Figure 1. Tensile test result for DP 980 steel with intermediate unloading cycles

3.2 Determination of Interpolation Coefficient

In the second ANN, the input and output data of the network are formed based on the regenerated curve in Figure 2b. An interpolation model is applied to interpolate the range between E_{av} and E_0 at every normalized stress point (σ_1/σ_0) as shown in Eq.(1).

$$C_e = \frac{E_c - E_{av}}{E_0 - E_{av}} \tag{1}$$

where σ_1/σ_0 and C_e are the input and output of the network training.

Table 1. Neural network training parameters

Parameters	Case 1	Case 2
Training function	Trainlm (LM)	Trainlm (LM)
Hidden layer	3	3
Neuron per layer	20, 20, 20	2, 2, 2

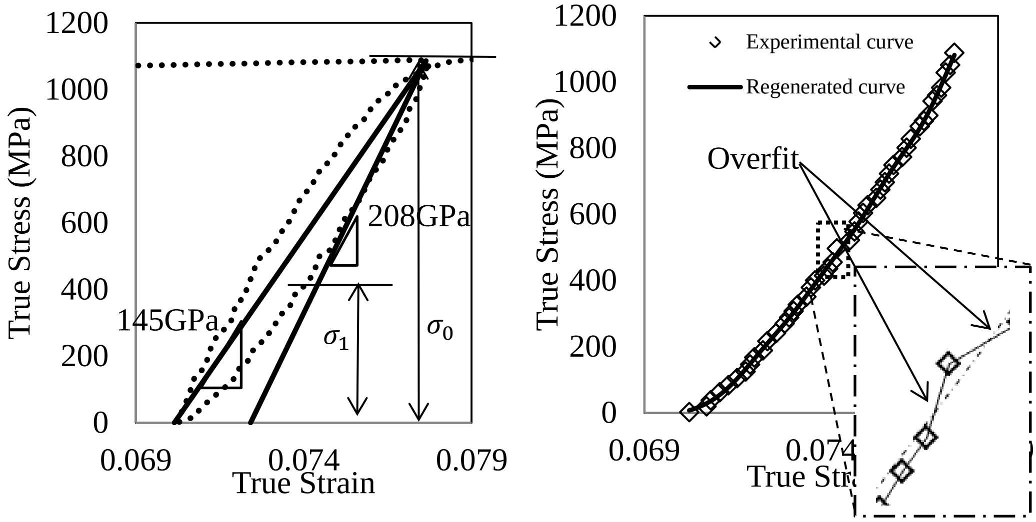

Figure 2. (a) Magnified view of the fourth unloading-reloading with E_0 and E_{av} (Sun and Wagoner 2011) (b) new unloading curve regenerated by first ANN

3.3 ANN to FE analysis link establishments

The second ANN is completely trained and the neuron weights and biases are extracted in the form of matrices. A feedforward network from the matrices is implemented into the user defined material subroutine. In the FE analysis, E_c need to be updated at every increment of the unloading/reloading process. The function of the feedforward-network-based constitutive model in the FE model at every increment is as follows:

(i) For (*i* +1)th strain increment, the input of the network is the value of the normalized stress point, σ_1/σ_0, where σ_1 and σ_0 are given by the current stress and current yield stress. To distinguish the input between unloading and reloading processes, the input is expressed as $(1-\sigma_1/\sigma_0)$ and (σ_1/σ_0).

(ii) E_c is then calculated by reversing Eq. (1) as:

$$E_c = C_e * (E_0 - E_{av}) + E_{av} \quad (2)$$

Results and Discussion

The variation of the unloading elastic modulus is a function of plastic pre-strain and it contributes to the size of hysteresis loops, as shown in Figure 1. Therefore, ANN prediction of the unloading curve cannot be utilized in the constitutive model if it is only based on the true strain and true stress as the input and output of the network.

This is due to the stresses along the unloading curve that need to be updated at every iteration as a product of E_c and true strain. By determining the relation of E_c with E_0 and E_{av} at the fourth loop, the product of Eq.(1) is able to represent all other loops based on the provided E_0 and E_{av}.

Figure 2b shows the result of the curve regeneration which consists of a closely fitted curve and a highly fitted curve by the first ANN. This fitting accuracy has a significant effect on the architecture of the second ANN. In the first case, the first ANN regenerates the unloading curve with high accuracy. A fluctuating step curve is produced when the slope determination is based on the highly fitted unloading curve, as shown in Figure 3a. In the second ANN part, high accuracy is essential as the result was utilized directly into the FE analysis. Therefore, a network training with a highly fitted training set requires 20 neurons in its first, second, and third hidden layer. This network consumes a very high computational cost and time. Furthermore, the prediction of C_e experiencing distortions at every step curves, as shown in Figure 3b. The distortions are the source of error when the predictions were transferred into FE analysis.

In the second case, the first ANN regenerates the unloading curve with a closely fitting accuracy and it results in quite a smooth curve, as shown in Figure 4a. In order to obtain such a smooth curve, the selection of network architecture with low number of neurons is essential, which determines the accuracy of the model with regard to the particular set of data. In the second ANN part, a network training with a closely fitted training set only requires eight neurons in its first, second, and third hidden layer, which results in low computational consumption. In addition, the prediction of C_e experiencing a smooth mapping, as shown in Figure 4b.

Figure 5 shows a comparison of the overall fit by the FE analysis using the current model with the experimental data. Although the network training was based on the fourth cycle, the overall prediction fit obtained was adequate. The result also shows that a closely fitting ANN prediction was adequate to achieve closeness to the experimental data in the FE analysis.

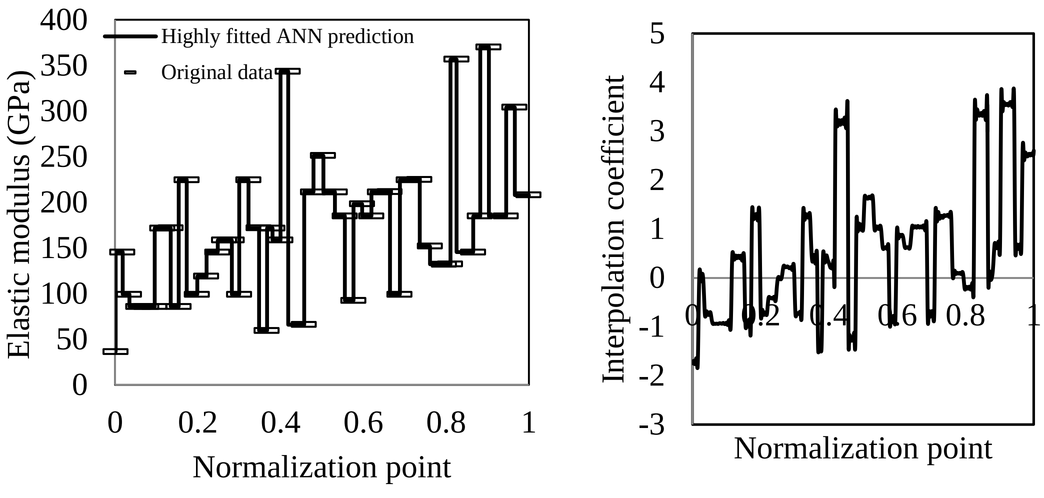

Figure 3. Case 1:(a) Elastic modulus determination;(b)interpolation coefficient prediction

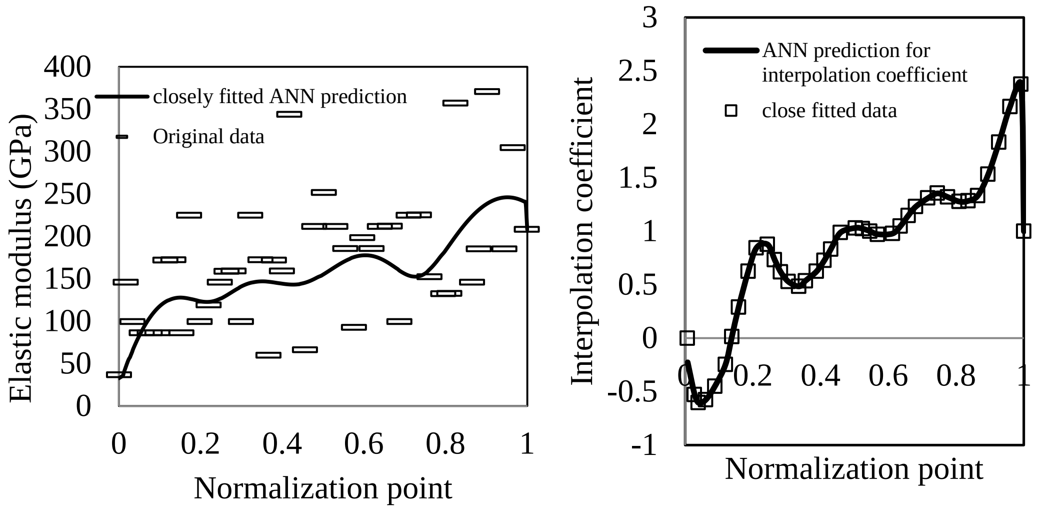

Figure 4. Case 2:(a) Elastic modulus determination;(b)interpolation coefficient prediction

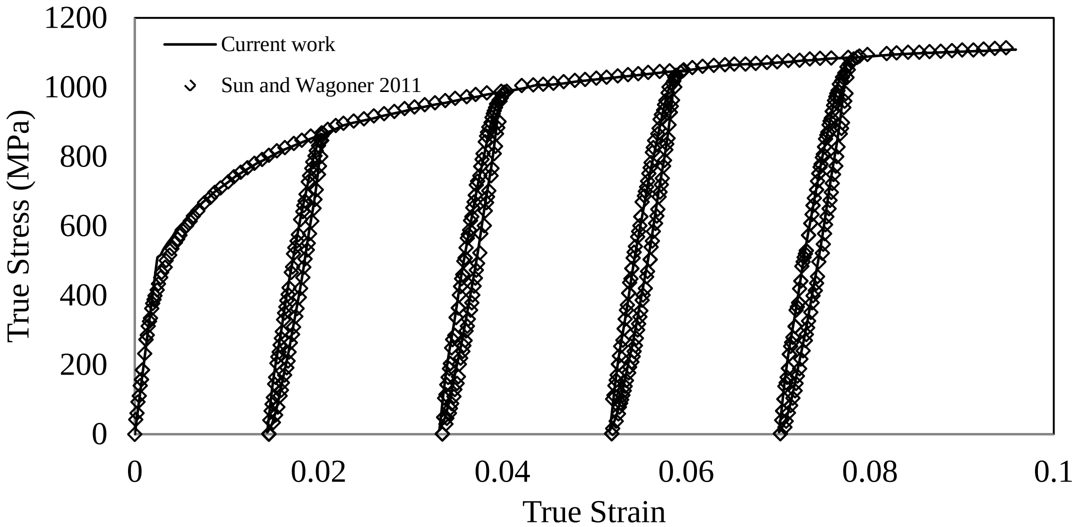

Figure 5. Comparison of overall fit by the FE analysis by using ANN prediction model

Conclusions

The above work demonstrates the ability of ANN to predict the relation between the nonlinear elastic modulus, the initial Young's modulus, and the chord modulus. It is shown that the model is well implemented in the finite element analysis to achieve closeness to the experimental data. With its generalization, this approach is suitable to be used in other finite element model of sheet metal forming to predict springback.

References

Aguir, H., BelHadjSalah, H., et al. (2011), Parameter identification of an elasto-plastic behaviour using artificial neural networks-genetic algorithm method. *Materials & Design* 321, pp.48-53.

Aguir, H., Chamekh, A., et al. (2008), Identification of Constitutive Parameters using Hybrid ANN multi-objective optimization procedure. *International Journal of Material Forming* 10, pp.1-4.

Andar, M. O., Kuwabara, T., et al. (2010), Elastic&Plastic and Inelastic Characteristics of High Strength Steel Sheets under Biaxial Loading and Unloading. *ISIJ International* 504, pp.613-619.

Cáceres, C. H., Sumitomo, T., et al. (2003), Pseudoelastic behaviour of cast magnesium AZ91 alloy under cyclic loading–unloading. *Acta Materialia* 5120, pp.6211-6218.

Chatti, S. and Hermi, N. (2011), The effect of non-linear recovery on springback prediction. *Computers & Structures* 8913-14, pp.1367-1377.

Cleveland, R. M. and Ghosh, A. K. (2002), Inelastic effects on springback in metals. *International Journal of Plasticity* 185-6, pp.769-785.

Eggertsen, P.-A. and Mattiasson, K. (2010), On the Modeling of the Unloading Modulus for Metal Sheets. *International Journal of Material Forming* 30, pp.127-130.

Kazan, R., Firat, M., et al. (2009), Prediction of springback in wipe-bending process of sheet metal using neural network. *Materials & Design* 302, pp.418-423.

Kim, H., Kim, C., et al. (2013), Nonlinear elastic behaviors of low and high strength steels in unloading and reloading. *Materials Science and Engineering: A* 5620, pp.161-171.

Li, X., Yang, Y., et al. (2002), Effect of the material-hardening mode on the springback simulation accuracy of V-free bending. *Journal of Materials Processing Technology* 1232, pp.209-211.

Sun, L. and Wagoner, R. H. (2011), Complex unloading behavior: Nature of the deformation and its consistent constitutive representation. *International Journal of Plasticity* 277, pp.1126-1144.

Veera Babu, K., Ganesh Narayanan, R., et al. (2010), An expert system for predicting the deep drawing behavior of tailor welded blanks. *Expert Systems with Applications* 3712, pp.7802-7812.

Yoshida, F., Uemori, T., et al. (2002), Elastic–plastic behavior of steel sheets under in-plane cyclic tension–compression at large strain. *International Journal of Plasticity* 185-6, pp.633-659.

Zhu, Y. X., Liu, Y. L., et al. (2012), Development and application of the material constitutive model in springback prediction of cold-bending. *Materials & Design* 420, pp.245-258.