



Integration of feedforward neural network and finite element in the draw-bend springback prediction



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ABSTRACT

To achieve 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 alternative modelling method able to facilitate nonlinear recovery was developed for springback prediction. The nonlinear elastic recovery was processed using back-propagation networks in an artificial neural network (ANN). This approach is able to perform pattern recognition and create direct mapping of the elastically-driven change after plastic deformation. The FE program for the sheet metal springback experiment was carried out with the integration of ANN. The results obtained at the end of the FE analyses were found to have improved in comparison to the measured data.

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1. Introduction

Sheet metal forming has been used widely in the manufacturing industry, especially in the automotive manufacturing sector. One of the main problems faced in the sheet metal forming process is the springback phenomenon. The occurrence of springback after the formation process results in inaccuracy of the final dimensions for a particular product. For decades, springback prediction techniques have been studied using the finite element (FE) method to replace the testing (trial and error) procedure in order to reduce the time and cost of analysis. Prediction by the FE method requires a deep knowledge of several factors that influence the final result of the analysis such as the friction coefficient, mesh density, material constitutive model, and so on. The material constitutive model is one of the most important factors that influence the accuracy of sheet metal springback prediction by the FE method (Eggertsen & Mattiasson, 2011). Although proper utilisation of yield criteria and hardening laws is essential to accurately reproduce the material flow stress, the accuracy of the simulation of elastic unloading behaviour remains a significant factor for the end result of sheet metal springback. This is due to the nonlinearity of elastic unloading that occurs during the springback process after the forming load is released from the metal strips.

The development of an additional surface in the yield surface (Eggertsen & Mattiasson, 2010b) and the transition of the elastic

to the plastic model (Quasi-Plastic–Elastic model) (Sun & Wagoner, 2011) have been proposed for the description on nonlinear elastic recovery in constitutive modelling. 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 & Hermi, 2011; Zhu, Liu, Yang, & Li, 2012).

An artificial neural network (ANN) is a mathematical model that attempts to mimic the large amount of interconnections of the biological neurons in the human brain to perform a complex processing task. The behaviour of complex experimental data can be predicted by developing a neural network model with sufficient input data. In the past years, the applications of ANN in the field of sheet metal forming have been used as inverse techniques by utilising FE analysis to predict parameters for established constitutive models. Aguir, BelHadjsalah, and Hambli (2011) proposed a hybrid optimization strategy based on an FE method, ANN computation, and genetic algorithm (GA) to identify the Karafillis and Boyce criterion, and the Voce law hardening parameters. Aguir, Chamekh, BelHadjsalah, Dogui, and Hambli (2008) used ANN to identify the parameters which reduce the difference between the FE method and the experimental measurements. Veera Babu, Ganesh Narayanan, and Saravana Kumar (2010) developed an ANN model to predict the deep drawing behaviour using a large set of data from simulation trials. Kazan, Firat, and Tiryaki (2009) investigated springback in the wipe-bending process, developing an ANN model based on data obtained from FE analysis.

Instead of utilising FE to provide training data, ANN models have also been used for mapping input and output parameters based on a large set of experimental measurements. Baseri, Bakshi-Jooybari, and Rahmani (2011) proposed a new fuzzy

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Nomenclature

FE	finite element	σ	true stress
ANN	artificial neural network	τ	shear stress
GA	genetic algorithm	ε	true strain
E_0	initial Young's modulus	γ	shear strain
E_{av}	chord modulus/variation of unloading modulus	λ	Lamé's first parameter
E_c	current elastic modulus	μ	shear modulus
σ_1/σ_0	stress normalisation point	E	elastic modulus
σ_1	current stress	ν	Poisson's ratio
σ_0	current yield stress	F_b	back force
C_e	interpolation coefficient		

learning back-propagation (FLBP) algorithm to predict the spring-back. The model was trained using the data generated based on experimental observations. Narayanasamy and Padmanabhan (2010) compared regression modelling and ANN for predicting springback in a steel sheet. In other metal-forming fields, there are several reports on the application of ANN to model complex constitutive models without any implementation of ANN-based constitutive models in FE code (Ji, Li, Li, & Li, 2010; Jing, 2011; Lin, Zhang, & Zhong, 2008; Lu et al., 2011; Sun et al., 2010; Toros & Ozturk, 2011; Zhu, Zeng, Sun, Feng, & Zhou, 2011).

The disadvantages of the FE inverse technique are that the end results are limited to the FE code capability, and a large number of simulation data are required. On the other hand, ANN prediction that is based on experimental measurements cannot be used in the FE simulation. At the same time, a large number of experimental data are required, resulting in a high experimental cost. These problems can be solved by utilising ANN as a constitutive model or a part of it in an FE analysis. In the wide engineering spectrum, several researchers have implemented it in their works (Haj-Ali & Kim, 2007; Yun, Ghaboussi, & Elnashai, 2008a; Yun, Ghaboussi, & Elnashai, 2008b). Jung and Ghaboussi (2006) reported the formulation of a rate-independent ANN-based material model for concrete and its implementation in FE software through a user-defined material subroutine (Abaqus-UMAT). Kessler, El-Gizawy, and Smith (2005) developed an ANN based material model for 6061 aluminium in the FE analysis of metal forging process through a user-defined material subroutine (Abaqus-VUMAT). Despite these applications, the technique has not yet been applied in the nonlinear recovery of sheet metal springback.

The objective of this paper is to develop a model that can predict the nonlinear elastic recovery through a soft computing approach, and that will be practically useful as part of a material constitutive model in FE analysis. In the present work, an ANN model is developed to predict the relationship of the nonlinear unloading modulus after a range of plastic pre-strains. The trained network model is integrated with the FE code through a user-material subroutine. The accuracy of the present work was validated with simulation results of the draw-bend springback test.

2. Principle of nonlinear elastic recovery

Most of the current FE method practises still utilise classic elastoplasticity theory, which assumes that the unloading modulus after plastic deformation is parallel to the initial Young's modulus (E_0). However, several investigations have shown that the unloading modulus is influenced by accumulated plastic strain (Andar, Kuwabara, Yonemura, & Uenishi, 2010; Cleveland & Ghosh, 2002; Eggertsen & Mattiasson, 2009a, 2009b; Li, Yang, Wang, Bao, & Li, 2002; Yang, Akiyama, & Sasaki, 2004; Yoshida, Uemori, & Fujiwara, 2002). A decreasing unloading modulus with increasing pre-strain can be observed with a given saturated value after a large

pre-strain is applied. The degradation of the unloading modulus with respect to the plastic pre-strain is represented by an exponential formula which is known as the chord modulus (E_{av}). This formula was further used by several studies to produce more accurate springback prediction results (Chatti, 2010; Eggertsen & Mattiasson, 2009a, 2009b, 2010a, 2010b, 2010c; Yoshida & Uemori, 2003; Yu, 2009).

Although E_{av} has been widely used by many researchers, several investigations have found that the unloading stress–strain curve actually shows nonlinear elastic recovery (Andar et al., 2010; Cleveland & Ghosh, 2002; Cáceres, Sumitomo, & Veidt, 2003). Fig. 1 shows the nonlinear unloading stress–strain curve with respect to E_σ and E_{av} . After plastic deformation to point A, the unloading process begins at point A and ends at point C according to E_0 , which describes the linear elastic recovery. On the other hand, the application of E_{av} results in point B as the end of the unloading process. However, the nonlinear curve AB is the actual unloading path that describes nonlinear recovery. To obtain an accurate springback prediction, the simplification of the nonlinear recovery is adequate if the springback phase achieves a relaxation in the total stresses. Nevertheless, generally at the end of the springback phase, the stresses produced in the forming phase decrease but remain as residual stresses, which confirms the requirement for nonlinear recovery modelling in springback predictions (Eggertsen & Mattiasson, 2010b).

3. Methodology

To generate the link between FE code and ANN, the application of ANN was split into the curve regeneration and interpolation coefficient parts, as shown in Fig. 2. A new curve was generated

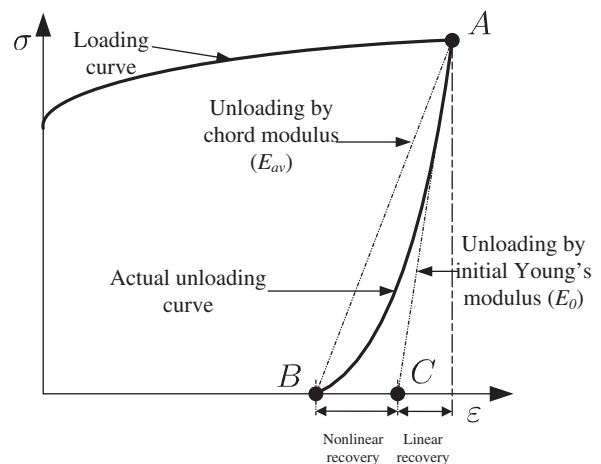


Fig. 1. Linear and non-linear unloading stress–strain curves.

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