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A New Technique of Springback Prediction by Combining FEM Calculation and Artificial Neural Network

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ABSTRACT

The study of deformability of metal sheets subjected to complex deformation states has become a topic of present interest; this fact is also a consequence of the emergence of new materials meant for auto bodies fabrication, whose forming processes imply knowledge about the influence of their modified mechanic characteristics on their behaviour during the deformation, and also on the quality of products. By predicting the quality of a formed product it is possible to evaluate the measure of the influence of its errors on the functioning of the final assembly the product belongs to. The paper presents a method to predict springback using the knowledge discovered and recorded after one experimental test is set up. The neural network method is used for prediction of the springback that offer a perfectible and dynamic model which can be enriched with new experimental or FEM simulation data.
Keywords: *springback prediction, artificial neural network, experiment*

1. Introduction

In bending and stamping processes, springback is an inherent phenomenon and its control is difficult to be carried out. In the same time, springback is a characteristic factor in estimating the quality of complex formed products.

Therefore, the springback prediction is an important objective of the equipment designers in the automotive industry.

The estimation of springback in material forming by economic and efficient methods allows to give up some progressive trial phases and redesigning of the bending and stamping equipments. Finally, the gain of the springback prediction is the decrease of the product price and the improvement of its quality. Recently, the researches are focused on finding springback compensation methods that skip the real tests and FEM simulations. There are authors dealing with data mining, genetic algorithms and neural network. The discovery of knowledge of the effects of geometry and process parameters on springback from FEM results becomes increasingly important, as the number of numerical simulation has grown exponentially. Data mining is an effective tool to realise knowledge discovery in simulation results [1, 2]. Using neural network in prediction of the springback is used to estimate the dimensions of the tools, the path of the bending and optimum trace to obtain a part [3, 4, 5].

In this context, the paper presents a technique to predict springback using the knowledge discovered and recorded after one experimental test is set up. The neural network method is used for prediction of the springback that offers a perfectible and dynamic model which can be enriched with new experimental or FEM simulation data.

2. Set up of the draw bending test

The experimental results have a great importance within a validation procedure of a numerical simulation program. The experimental test selected for the evaluation of the springback dimension for the taken into account was the Draw Bending Test [6, 7].

The test simulates the stresses state in a bending process and emphasises the springback parameters in the XZ plan and also its dependency to the joining radius of the tools. This test is useful in the experimental validation of the version Backstress of ITAS3D.

The profile necessary for comparing the simulation results with the experimental results was obtained by deforming specimens of materials within the Draw Bending test and then by measuring them using a three-dimensional digitizing system.

Materials were selected from the category of materials used within car makers industry: advanced generation high strength steels.

The use of these materials within forming processes and especially within their numerical simulation required knowledge referring to their mechanical and technological characteristics, obtained in frame of several basic mechanical tests: tensile test, shearing. A database for these materials was generated in this way. The algorithm for obtaining the data contains mechanical tests, filtering of the experimental data and identification of the coefficients.

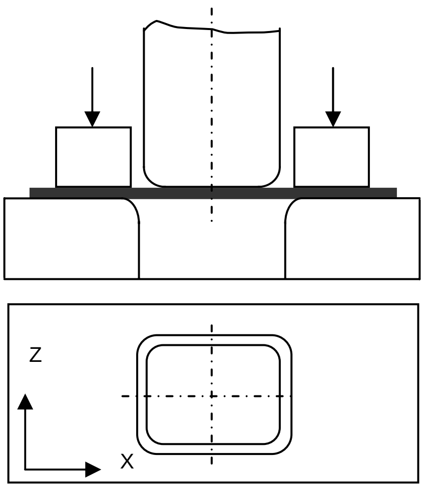

Figure 1 - Scheme of the hat bending test

3. Identification of the saturated material models coefficients

Tests carried out on high strength steel HS590 are monotonic uniaxial tensile test, monotonic shearing test and cyclic Bauschinger 20 %, 40 % tests.
Filtering of the raw curves supposes elimination of the noises of the curves and also the elastic part. This is reasonable due to the fact that in metal forming only the large plastic strains are important.
Using identification of the saturation law as

$$\overline{\sigma}_e = Y_0 + R + f \cdot S \quad (1)$$

where: Y_0 is the yielding stress, R internal variable of the material which describe the arrangement of the dislocation, S is internal variable of material which describe the directional resistance of the dislocation structures, f is a parameter taking values between 0 and 1, without contributions in the dislocation structures adjustment.

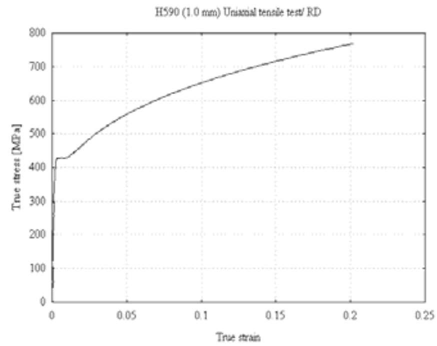

Figure 2 - True stress - true strain curve in tensile test

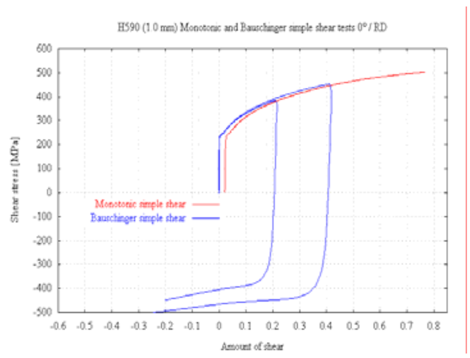

Figure 3 - Shearing and Bauschinger curves

It is of a major importance in the large deformation theory in order to explain the forming of some microplastic states. X has a contribution to the yielding of the material by its direction, that means X can favours the plastic yielding in one direction and can be opposite comparing to the direction of yielding. X allows to describe the rapid changes in path deformations [8].

When backstress is taken into account is the modification of the stress-strain curve during deformation, because X itself has an evolution which determines a decreased curve of the equivalent stresses.

Kinematic hardening is considered to have an evolution described by the following expression

$$\dot{\underline{\hat{X}}} = C_X \cdot \left[\frac{X_{sat}}{\overline{\sigma}_e} \cdot (\underline{\hat{\sigma}}' - \underline{\hat{X}}) - X \right] \cdot \dot{\lambda} \,. \quad (2)$$

Kinematic hardening is taken into account together with saturation law which was implemented in ITAS3D software. A new version of ITAS3D - Mesh version - was elaborated in order to be used in the simulation of springback. The coefficients carried out from identification which fit the experimental curves, carried out within the identification aided by SiDoLo [LPMTM, Université Paris 13, France] software, are: Y_0 = 324 MPa; R_{sat} = 353 MPa; C_R = 2.95; X_{sat} = 155.8 MPa; C_X = 36.5 - for kinematic hardening law and C = 1068.00 , n = 0.196, e_0 = 0.0024 for isotropic hardening type Swift law.

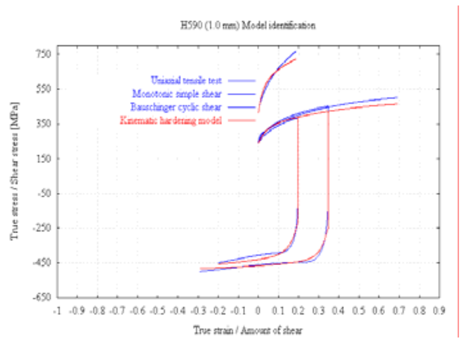

Figure 4 - Material model identification

4. Numerical simulation of springback in draw bending test

ITAS3D software has a static explicit scheme of integration and an algorithm for cancelling the nonequilibrated forces. The springback is more prominent at the high strength steels, so that HS590 (high strength steel) is used in these simulations. In order to predict the springback in the draw bending test of the HS 590 material the simulations were made with strictly the same conditions like in the experiment. These are the following:_Geometry of the test was rectangular shape for the punch and the die; punch cross section dimensions: 67.4 x 96.4mm, joining radius of the die of 5 mm; die cross section dimensions: 70x100 mm, joining radius of the punch of 5mm; clearance between punch and die of 1.3 mm; blank size 50x215mm; punch stroke 45 mm; blank holder force 120 daN; blank thickness 1mm.

The numerical conditions are: software ITAS3D with a new algorithm for cancelling the unequilibrated forces and with the possibility to consider the backstress [9]. Finite element used is a reduced integration scheme with 7 integration points. The size of the element was 4.3 (2500 elements for all the blank). Anisotropy coefficients of HS590 are $r_0{}^{o}$ = 0.848, $r_{45}{}^{o}$ = 0.799 and $r_{90}{}^{o}$ = 1.026.

In order to illustrate the very significant improvement in modelling and simulating the backstress effect due to the implementation of saturation model in a version of ITAS3D finite element software, which contains the algorithm of cancelling the nonequilibrated nodal forces, in the figure 5 it is presented a comparison between experimental results and the results obtained by numerical simulation with Swift law (a) and with Saturation law considering backstress component (b).

Since the simulation results obtained by FEM calculation fits very well the experimental results, following only simulation can be done in order to obtain the values of the springback and to build the data matrix for the neural network. Backstress component has an important role in springback calculation by FEM analysis. After setting up an accurate set of materials coefficients for identification of the constitutive model, FEM calculation is enough to generate the data for training one neural network.

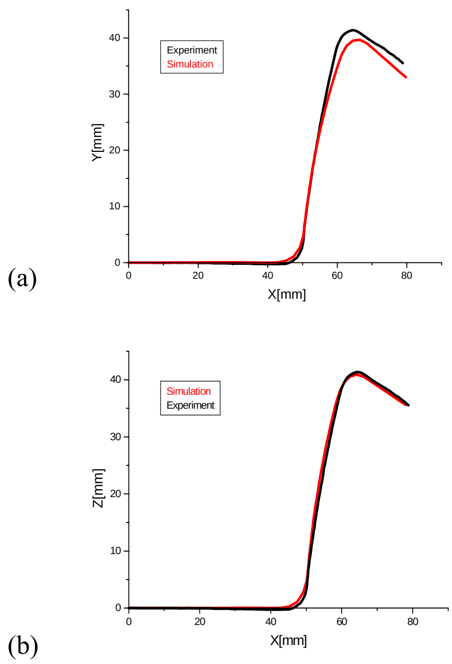

Figure 5. Comparison of the numerical simulation results and experimental results – Kinematic Hardening Model

5. The model of neural network for springback prediction

We consider the backstress of thin blanks as exit variable for the neural network.
The values of elastic reset have been calculated for 11 bending cases, but finding the value of this variable for another numerically non-simulated case can be done by interrogation of corresponding neural network.

The functioning mode of the neural network can bring about an improvement in the approximation obtained by a mathematical model, as it establishes relations between inputs and outputs, based on statistical criteria. If the network is used to values calculated with high precision, then the predicted results will also show high precision.

By interrogating a neural network set up for thin blanks deformation, it may be improved tension states located within the deformation areas, by choosing an optimal geometry, thus avoiding critical stresses that determine the apparition of significant backstress.

In order to diminish the error by which a neural network estimates the size of backstress, this must be trained with values closest as possible to reality.

In figure 6 it is shown the algorithm of managing a procedure for finding a solution for think blanks deformation, with the aim of decreasing the risk of rejected parts.

The experiment may be substituted by numerical simulation with finite element but, by training a neural network with these known values, prediction of backstress values for known input values can be predicted, on condition that the interrogation values of the network to fall within the variation intervals of known input values.

Informal values of backstress may be found for a material or for some cinematic conditions, only by interrogating the network trained with the values determined by experiment and by numerical simulation.

6. Prediction of the springback using artificial neural network

Improvement of the backstress calculation precision for the bending case in fig. 1 was used in generating a data set which, together with those generated by the experiment, form the database of the neural network NNModel. The neural network model has as input variables the following: tensile resistance [277-720] N/mm^2, yielding resistance [147-387] N/mm^2, anisotropy [0.88-2.52], material thickness [0.7-1.2] mm, the radius of joining the material to active blank [3-10] mm, blankholder force [75-600] daN, and as output variables the springback angle [θ_1], [θ_2] in degrees, according to Numisheet 93[10].

The training parameters of the neural network were established on the basis of some sensibility studies of their influence on output values prediction.

The neural network employs the backpropagation method and the stop-during-operating criterion is the tolerance imposed on by predicted backstress.

Operating parameters of the network are shown in figure 6. The name of the trained neural network is NEUROSPRING. The algorithm of the NEUROSPRING trained network is presented in figure 7.

Training of the neural network is performed in two stages - one is the network initialisation and the second is the training. The training is done until the imposed tolerance is reached.

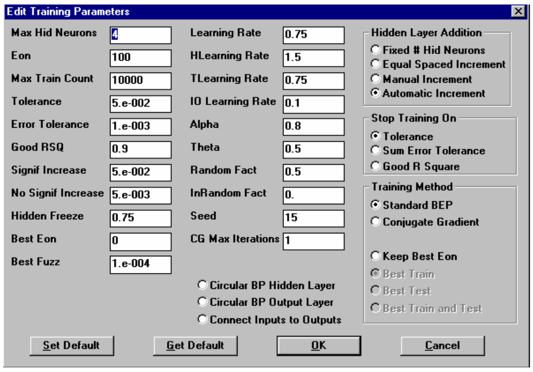

Figure 6 Setting parameters of the NEUROSPRING

7. Interrogation of the NEUROSPRING

Once accustomed to the neural network, its interrogation with unknown values during training but still possible during design – on condition that these values fall within the variation interval of training variables – leads to a drastic diminution of the design stage for a deformation equipment. One example of interrogation using the input case as following: metal sheet thickness of 1 mm for a material showing the tensile resistance 498 N/mm^2 and yielding resistance 350 N/mm^2, automatically leads to finding the springback values given by θ_1 of 2.032^o and by θ_2 of 111.102 ^{o}.

This is how, without numerical simulation of experimenting, the value of springback for a material with characteristics falling within the training intervals can be found. In this case, the springback prediction

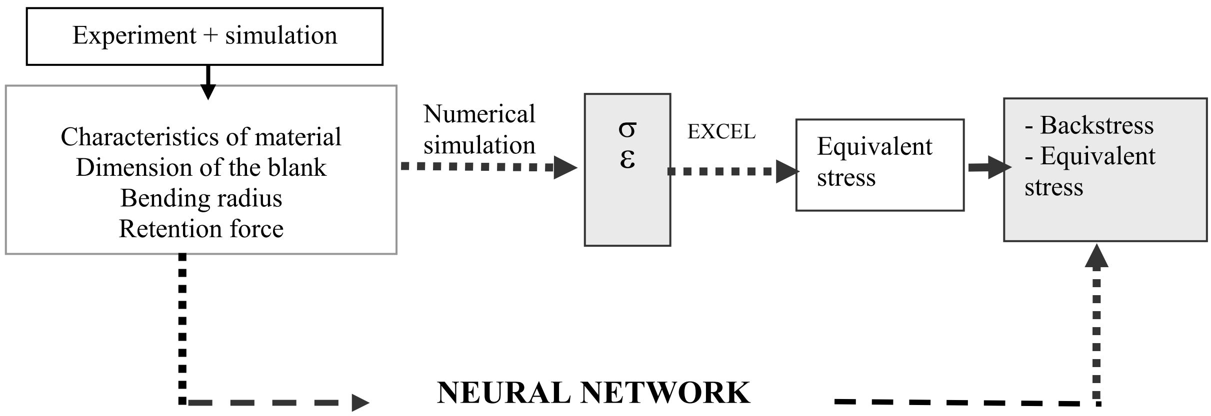

Figure 7. The algorithm of springback prediction by using artificial neural network

precision is of 10^{-3}, which is acceptable as compared to the backstress values.

The value of the predicted springback is the more accurate the precise the training data. This is why the first goal of this paper was to identify the parameters influence for a material submitted to high precision numerical simulation.

8. Conclusions

The new materials have to be characterised by internal variables that describe more precisely the evolution of the microstructure during the deformation.

Springback plays a major role in large deformation theory for explaining the rapid changes in the flow stress following a strain-path change, e.g. in the case of springback.

By introducing of the algorithm of cancelling nonequilibrated forces and the Teodosiu-Hu constitutive model, the springback in advanced thin metal forming processes could be evaluated with an accuracy of 95%. A more precisely characterisation of the materials led to correction of the shapes after springback in metal forming processes.

Artificial neuronal network is an useful method in predicting the values of the springback when a search space is generated by experiment and accurate simulated results.

In this paper, an algorithm of combining finite element simulation and artificial neural network was used to simplify the prediction of the springback in the case of the hat bending test.

The neuronal network trained with the known data is a dynamic model which can be continuing improved. It is an interactive instrument that is perfecting by increasing the number and size of the input data.

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Die prognose des springback mit dem künstlische neuronale netzwerke und der numerische simulation

Zusammenfassung

Die Studie von deformability von komplizierten Deformierungszuständen unterworfenen Metallplatten ist ein Thema vom gegenwärtigen Interesse geworden. Diese Tatsache ist auch eine Folge des Erscheinens von neuen für die Auto-Körperherstellung beabsichtigten Materialien. Sich formende Prozesse dieser Teile beziehen Kenntnisse über den Einfluss ihrer modifizierten mechanischen Eigenschaften auf ihrem Verhalten während der Deformierung, und auch auf der Qualität von Produkten ein. Die Qualität eines tiefgezogenen Produktes voraussagend, ist es möglich, das Maß des Einflusses seiner Fehler auf der Wirkung des Endzusammenbaues zu bewerten, dem das Produkt gehört. Die Arbeit präsentiert eine Methode für das springback Prognose wird dem Verwenden der Kenntnisse vorauszusagen und das küsntlische neuronale netzwerke gebraucht.

Predicția revenirii elastice utilizând modelarea cu element finit combinată cu metoda rețelelor neuronale

Rezumat

Studiul deformabilității tablelor subțiri supuse deformării complexe este un subiect de actualitate, fiind o consecința a faptului ca sunt create noi materiale pentru fabricarea caroseriilor auto. Procesele de deformare asociate fabricării caroseriilor auto implica cunoaşterea influenta caracteristicilor mecanice modificate ale acestor materiale asupra deformării si asupra calității produselor. Prin predicția calității pieselor deformate este posibil sa se evalueze măsura in care erorile de prelucrare influențează funcționarea in ansamblul din care face parte. Lucrarea prezintă o noua tehnica de predicție a revenirii elastice utilizând baze de cunoaştere extrase din experiment si din simulare numerica. Este utilizata o rețea neuronala pentru predicția revenirii elastice ce utilizează date furnizate de simularea numerica realizata cu precizie ridicata fata de un experiment propus, prin identificarea unui model constitutiv de material ce tine seama de evoluția microstructurii in timpul deformării.