Identification of Constitutive Parameters using Hybrid ANN multi-objective optimization procedure

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ABSTRACT: This paper deals with the identification of material parameters for an elastoplastic behaviour model with isotropic hardening using several experimental tests at the same time. But, these tests are generally inhomogeneous and finite element simulations are necessary for their analysis. Therefore an inverse analysis is carried out and the identification problem is converted into a multi-objective optimization where prohibitive computing time is required. We propose in this work a hybrid approach where Artificial Neural Networks (ANN) are trained by finite element results. Then, the multi objective procedure calls the ANN function in place of the finite element code. The proposed approach is exemplified on the identification of non-associative Hill'48 criterion and Voce parameters model of the Stainless Steel AISI 304.

Key words: Inverse identification, Multi-objective optimization, Artificial Neural Network, Bulge test, Plane test, Non-associative plasticity

1 INTRODUCTION

The numerical simulation brings an appreciable help in the control of metal forming process. Indeed, one can virtually carry out complex processes, which significantly contributes to their optimization. But the relevance of the results depends broadly on the consistency of the materials behaviour models used in the simulation of forming process [1]. Although, several softwares are available today and allow the numerical simulation of the metal forming processes, some efforts are still required to improve the considered behaviour models and to identify them in the most correct way.

For this reason and considering the complexity of loading paths undergone by the material during its forming, the tensile test is not enough any more and additional information are to be found from other tests like plane test (tensile test with a wide specimen), simple shear or bulge test [2]. So, the identification becomes more difficult. Indeed, it is generally rare that the parameters identified from one of the tests make it possible to find with a reasonable precision the results of the other tests. The aim of this work is situated in this context. Its goal is to identify the orthotropic elastoplastic behaviour model parameters with isotropic hardening of a material using several experimental tests. In this identification the plane test and the bulge test are considered in addition to the tensile test.

Because these tests are generally inhomogeneous, their finite element simulations are necessary. Therefore an inverse analysis is carried out and the identification problem is converted into a multi-objective optimization.

In order to reduce the computing time in the evaluation of the objective functions, we use the artificial neural networks (ANN) to substitute the finite element calculations. The training of the ANN is obviously made by finite element simulations of the experimental tests. Moreover, to reduce the number of simulations, we use the optimal experimental design.

The multi-objective optimization procedure used here is coupled to an ANN model in order to evaluate the objective functions which let the proposed approach more viable.

In the first step, we used a hybrid multi-objective optimization method to identify the Hill'48 criterion with the associative normality assumption and the Voce law hardening parameters of the Stainless Steel AISI 304. In the second step, we considered the orthotropic criterion of Hill'48 with the non-associative normality assumption. So the number of material parameters to be identified is increased.

The general outlines of the material models are presented in section2. The identification strategy is then presented in section 3. Section 4 and section 5 are devoted to the discussions of the results and to the conclusions respectively.

2 MATERIAL MODELS

The used models are based on the following formulations:

$$f(\sigma,\alpha)=\sigma_c(\sigma)-\sigma_s(\alpha)\leq 0 \quad (1)$$

Where $\sigma_c(\sigma)$ is the equivalent yield stress of the model and $\sigma_s(\alpha)$ is the isotropic strain hardening law. The equivalent yield stress is taken equal to the Hill's orthotropic yield criterion (Hill 1948). In general the plastic flow rule is written as follows:

$$\dot{\varepsilon}^p=\dot{\alpha}\frac{\partial\sigma_p}{\partial\sigma}\text{; with } \dot{\alpha}\geq 0\text{; } \dot{\alpha}\, f=0\text{ ; } \dot{\alpha}\, \dot{f}=0 \quad (2)$$

Where σ_p is the plastic potential function. Two cases are considered:

- First case: the potential function is equal to the equivalent yield stress $\sigma_p = \sigma_c$. It's usually called the associative plasticity.
- Second case: the potential function is different from the equivalent yield stress. It's the non-associative plasticity.

In the case of plane stress states, the yield stress function (Hill 1948) is given as follows:

$$\sigma_c^2=(G+H)\sigma_{11}^2-2H\sigma_{11}\sigma_{22}+(F+H)\sigma_{22}^2+2N\sigma_{12}^2 \quad (3)$$

Where σ_{ij} represents the Cauchy stress tensor in the orthotropic axes; F, G, H and N are the anisotropic coefficients. We introduce the condition $G + H = 1$, so that we have $\sigma_c = \sigma_{11}$ for the simple tensile test in the rolling direction.

The Lankford's coefficients are expressed against the anisotropic coefficients as follows:

$$r_0=\frac{H}{G}\text{ ;}\qquad r_{90}=\frac{H}{F}\text{ ;}\qquad r_{45}=\frac{2N-F-G}{2(F+G)} \quad (4)$$

In the non-associative plasticity, the plastic potential function σ_p has the same form as the criterion function. Therefore, we introduce a set of anisotropic parameters F', G', H' and N' as follows:

$$\sigma_p^2=(G'+H')\sigma_{11}^2-2H'\sigma_{11}\sigma_{22}+(F'+H')\sigma_{22}^2+2N'\sigma_{12}^2 \quad (5)$$

Also we consider that the plastic potential satisfy the condition $G' + H' = 1$.

The hardening law is fitted by the Voce expression:

$$\sigma_s(\alpha)=\sigma_0+R_{sat}\left[1-\exp(-C_R\alpha)\right] \quad (6)$$

Where σ_0 is the yield stress, C_R indicates the velocity stress evolution and R_{sat} indicates the stress level in the saturation behaviour.

Under the associative flow rule assumption and in the case of plane stress, the material parameters that will be identified are:

- Strain hardening curve $\sigma_s(\alpha)$: R_{sat} , C_R and σ_0;
- Lankford's coefficients: r_0, r_{45}, and r_{90}.

And under the non-associative flow rule assumption, we have to identify:

- Strain hardening curve $\sigma_s(\alpha)$: R_{sat} , C_R and σ_0;
- Criterion anisotropic coefficients: r_0, r_{45} and r_{90};
- Potential anisotropic coefficients: r_0', r_{45}' and r_{90}'

The experimental anisotropic coefficients of the plastic potential are identified from the Lankford's coefficients. The anisotropic criterion coefficients are identified from the strain hardening curve in all the available directions [3].

Table1 shows the experimental strain hardening constants, the criterion and the potential anisotropic coefficients in three directions with respect to the rolling one for the considered material.

Table1. The experimental material parameters

Hardening coefficients			Criterion coefficients			Plastic potential coefficients		
R_{sat}	C_R	σ_0	r_0	r_{45}	r_{90}	r_0'	r_{45}'	r_{90}'
1515	2.02	358	1.85	0.55	1.51	1.24	0.99	1.2

3 IDENTIFICATION STRATEGY

Classically, the inverse identification procedure consists of finding the parameters which minimize the difference between a calculated response by finite element method (FE) and the experimental response in a certain norm sense. In the proposed approach, FE simulations are carried out to build up two databases which will be used to train the artificial neural network models (ANN). So, FE simulations are no longer necessary because all knowledge is contained in the ANN models. Moreover, we use more than one test (tensile test, plane test and bulge test) to identify material parameters. Therefore, the problem of identification is converted into a multi-objective optimization to minimize the error between the experimental response of the considered tests and the predicted ones (by the ANN models).

In the first step, two neural networks are prepared: one for the plane test and one for the bulge test. So, finite element simulations of the experimental tests using systematically varied sets of material parameters are carried out in order to build two databases. Each simulation calculates the global response of each test of the corresponding set of material data. Then, the responses are normalised and stored in a database which is used to train the ANN models.

In this work, we identify six material parameters (R_{sat}, C_r, σ_0, r_0, r_{45}, and r_{90}) for the associative plasticity and nine material parameters (R_{sat}, C_r, σ_0, r_0, r_{45}, r_{90}, r_0', r_{45}' and r_{90}') for the non-associative plasticity.

The number of FE simulations can be reduced by considering an optimal experimental design called Taguchi design. In this case, the two numerical databases (two optimal experimental designs) are generated by 27 FE simulations for each test.

In the second step, the ANN models predict the response of each test for a set of the material parameters data. After that, the material parameters can be obtained by an optimization routine to minimize simultaneously the gap between the experimental response and the predicted one for each test. For this reason a multi-objective optimization routine based on the "Goal Attainment Method"[4] coupled with an ANN model is adopted.

The multi-objective optimization can be formulated as follows:

$$\text{Minimise } \gamma \;, \gamma \in R, X \in \Omega \tag{7}$$

Such that

$$\begin{cases} F_i(X) - w_i\gamma \leq F_i^* & i = 1,2 \\ x_k \in \left[x_{k\min} \quad x_{k\max} \right] \;; x_k \hat{I} X & k = 1,\ldots,6(or9) \end{cases}$$

$F_1(X)$ (respectively $F_2(X)$) is the error between the experimental and ANN model response for the bulge test (respectively the plane test). X represents the parameters to be identified; w_i is the weighting coefficient and F_i^* is the goal.

$$F_i(X) = \frac{1}{n}\sqrt{\sum_{l=1}^{n}\left(\frac{R_{il}^{\exp}(X) - R_{il}^{ANN}(X)}{R_i^{\exp}{}_{\max}}\right)^2} \tag{8}$$

Where $i=1,2$; n is the number of points of measurement and R is the force in the plane test and the pressure in the bulge test.

4 RESULTS AND DISCUSSIONS

The experimental material parameters are obtained from the simple tensile test. These parameters are used in finite elements simulations with the associative and non-associative plasticity of the bulge test and the plane test. The comparison of the experimental and numerical curves shows a large gap in the two tests. The aim of our identification is to find the values of the parameters which reduce the gap between these curves using the two tests at the same time. For this reason the identification strategy presented previously is applied. Its goal is to identify the material parameters in the case of associative and non-associative plasticity. The used multi-objective optimization routine is based on the principle of predominance of Pareto. The non dominated solutions which constitute the Pareto optimal fronts (Fig.1) are obtained using several trial values of w_i and considering $F_i^*=0$.

In order to find a non dominated solution, the algorithm of optimization carries out more than one hundred of iterations. It is specifically the interest of our method, since the use of ANN meta-model takes only a very low CPU time compared to the finite element calculation. (CPU_ANN<10^{-4} CPU_FE).

One can choose any non dominated solution from these fronts. As example, we select here the solutions S1 and S2 (S1: case of associative plasticity and S2: case of non-associative plasticity).

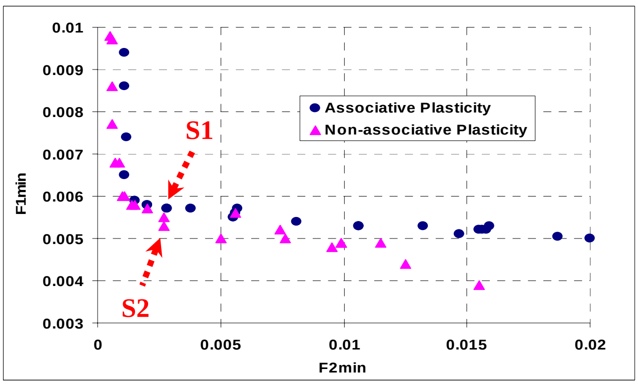

Fig. 1. Optimal solutions for the associative and non-associative plasticity

Table2 shows the comparison between the experimental and the identified material parameters for the chosen solutions.

Table2. The experimental and the identified material parameters

Material Parameters	Experimental Values	Identified Values S1	Identified Values S2
σ_0 (MPa)	358	275	269
R_{sat} (MPa)	1515	1098	1028
C_R	2.02	2.31	2.61
r_0	1.85	1.17	1.66
r_{45}	0.55	0.70	0.66
r_{90}	1.51	1.03	1.48
r_0'	1.24	-	1.47
r_{45}'	0.99	-	0.73
r_{90}'	1.20	-	1.32

To validate this approach, the set of material parameters corresponding to these solutions is used in a direct finite element simulation of two tests. The results of these simulations are presented in Fig.2 and Fig.3.

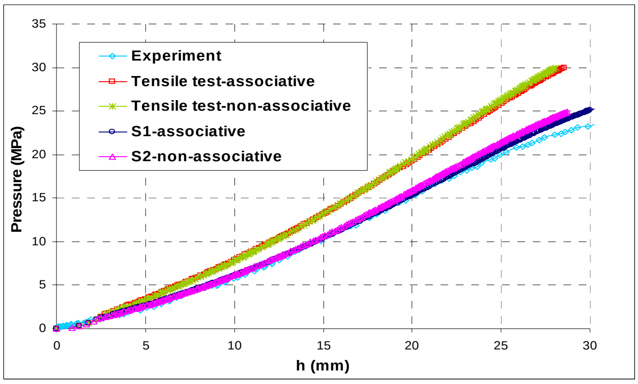

Fig. 2. Comparison between the responses of the bulge test

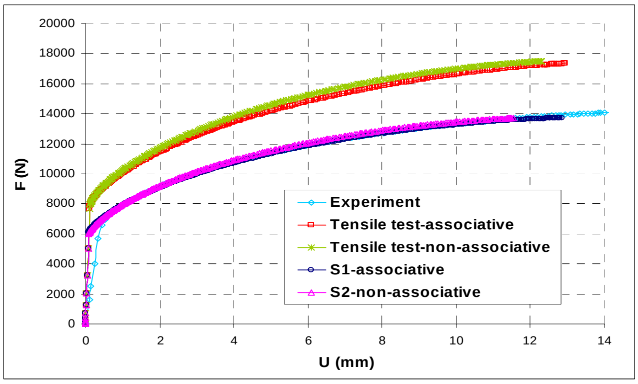

Fig. 3. Comparison between the responses of the plane test

It appears from these figures that the gap between the numerical and experimental responses of the proposed strategy for the first and the second solution is reduced in the two tests.
A weak amelioration of the results is shown using the plasticity model with non-associative normality assumption.

5 CONCLUSIONS

A hybrid method of multi-objective optimization coupled to ANN models is used to identify the parameters of the Hill'48 criterion and those of Voce hardening law using several experimental tests (plane tensile test and the bulge test). In this method the artificial neural networks (ANN) are used as an alternative to the finite element calculations in the evaluation of the objective functions. The training of the ANN is obviously made by finite element simulations of the experimental tests. The main advantage of this method is the very low CPU time that it requires compared to a classical inverse method.
This approach is used at first to identify the associative Hill'48 criterion and the Voce law hardening parameters of the AISI 304. In order to find more accurate results, the non-associative Hill’48 criterion is considered. The resultant fronts of Pareto show a weak amelioration of the results.
Therefore, we can conclude that the proposed hybrid multi-objective optimization procedure allows to identify more elaborate behaviour models and to determine the accurate ones. However, non quadratic criterion can be investigated.

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