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Material parameters identification: Gradient-based, genetic and hybrid optimization algorithms

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ABSTRACT

This paper presents two procedures for the identification of material parameters, a genetic algorithm and a gradient-based algorithm. These algorithms enable both the yield criterion and the work hardening parameters to be identified. A hybrid algorithm is also used, which is a combination of the former two, in such a way that the result of the genetic algorithm is considered as the initial values for the gradient-based algorithm. The objective of this approach is to improve the performance of the gradient-based algorithm, which is strongly dependent on the initial set of results. The constitutive model used to compare the three different optimization schemes uses the Barlat'91 yield criterion, an isotropic Voce type law and a kinematic Lemaitre and Chaboche law, which is suitable for the case of aluminium alloys. In order to analyse the effectiveness of this optimization procedure, numerical and experimental results for an EN AW-5754 aluminium alloy are compared.

1. Introduction

The numerical simulation of sheet metal forming processes has proven its efficiency and usefulness. In the last twenty years, considerable efforts have been made to improve the numerical methods for solving non-linear problems arising from material behaviour, geometry and friction. Moreover, by means of user-friendly graphical interfaces and due to increasing computer capacity, the use of numerical simulation to analyze the sheet metal forming process has been promoted at an industrial scale. Despite the advances in this domain, the final result of the simulation of metal forming processes depends greatly on the limitations of the constitutive material behaviour model, used in the simulations [1,2]. In fact, various types of models can be used, according to their ability to explain and/or predict the details of the plastic behaviour during a given deformation process. Simple models of isotropic hardening can give an acceptable estimate of the drawing forces occurring during the process and are widely used in industry [3]. However, more sophisticated models, involving for instance non-linear kinematic hardening and more refined yield criteria models, give improved evaluation of the evolution of every deformation process [4–7]. Generally, these models have a large number of parameters, which increases the amount and type of experimental tests necessary for their evaluation. Moreover, the results of the parameter evaluation are often inconsistent [8–10].

The identification of the material parameters, for a given constitutive model, can be seen as an inverse formulation. In this context, the key idea is to simulate the performed experiment, trying to adapt material parameters in order to numerically obtain the same results as the experimental ones [11,12]. This approach consists of an optimization problem where the objective function is to mini-

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mize the gap between the experimental and the numerical results. The optimization variables are the material parameters that appear in the constitutive model. To solve this problem one can use different methods that can be divided mainly into three groups:

1. Derivative-free search algorithms.
2. Gradient-based algorithms.
3. Evolutionary algorithms.

The derivative-free algorithms, also called direct search algorithms, are generally based on simple strategies and do not require the calculation of derivatives. Their simplicity is their main attribute. However, direct search algorithms undergo the problem of converging to local minimums, and are also somehow user-dependent. The convergence of these algorithms is very time-consuming and involves the comparison of each trial solution with the best previous solution. One can refer to several methods based on direct search strategies namely: pattern search [13], Rosenbrock [14], simplex [15] and Powell [16]. These methods remain popular because of their simplicity, flexibility and reliability.

The gradient-based algorithms usually converge quickly in the vicinity of the solution, and are therefore very interesting in terms of rapidity. However, they have some limitations, being strongly dependent on user skills, due to the need to choose the initial trial solutions. Also, they can easily fall to local minimums, mainly when the procedure is applied to multi-objective functions, as is the case with material parameter identification. The requirement of derivative calculation makes theses methods non-trivial to implement. One can mention a large number of optimization gradient-based methods such as the Steepest Descent Method, the Newton method or several Quasi-Newton Methods [17–20].

An *evolutionary algorithm* is a generic definition used to indicate any population-based optimization algorithm that makes use of some mechanism to improve the initial solutions. The trial solutions to the optimization problem are individuals in a population. Evolution of the population takes place after the repeated application of the genetic operators (reproduction, mutation, recombination, etc.). These algorithms have become very popular in recent years, mainly because of the increase in computer calculation speed that leads to optimized results in an acceptable time. Moreover, it is generally believed that evolutionary algorithms perform consistently well across all types of problems, which is evidenced by their success in fields such as engineering, art, biology, economics, genetics, robotics, social sciences and others. Although they are robust methods, their convergence is very time-consuming, and they must be considered as sub-optimal algorithms, as for continuous variable optimization the global minimum of the objective function is not guaranteed. Anyway, local minima are generally avoided and the final solution is in the vicinity of the global minimum. Genetic algorithms are the most popular type of evolutionary algorithms that make use of biological evolutionary analogies to improve the initial set of solutions.

In conclusion, these three types of approaches to variable optimization can be used to solve the problem of determining the material parameters of a given constitutive model. All the algorithms have advantages and drawbacks. However, one can produce hybrid algorithms combining the advantages of each approach, e.g. robustness of the genetic algorithm and performance of the gradient-based algorithm. Generally speaking, if the constitutive model is relatively simple e.g. isotropic hardening described by a power law and an anisotropic Hill'48 [21] yield criterion, the identification is relatively easy to perform, whenever the available experimental data is sufficient. As the complexity of constitutive models increases, identification becomes non-trivial, and generally demands user skills. To explore and identify the problems and difficulties that can arise during the parameter identification procedure, this paper makes use of two different algorithms, a gradient-based and an evolutive algorithm, to identify the material parameters of the constitutive equations model in the case of a 1 mm thick sheet of EN AW-5754-O aluminium alloy, used in the automotive industry. A set of experimental results was obtained from tension and both monotonic and Bauschinger shear tests. The Barlat'91 [22] yield criterion is considered. A Voce type equation [23] with kinematic hardening component described by the Lemaitre and Chaboche law [24] is used.

The paper is structured as follows. In Section 2, the constitutive equations are briefly illustrated. In Section 3 the parameter identification problem and the two algorithms used are presented. In Section 4 the experimental tests are described. In Section 5 the results of the parameters identified are discussed. And Section 6 sums up the main conclusions of this work.

2. Constitutive equations

The YLD91 yield criterion was proposed by Barlat et al. [22,25] and was written from previous isotropic criterion defined by Hershey and Hosford [26,27]. It can be written as follows:

$$\phi = |S_1 - S_2|^m + |S_2 - S_3|^m + |S_3 - S_1|^m = 2\bar{\sigma}^m \tag{1}$$

where S_1, S_2 and S_3 are the principal values of the isotropic plastic equivalent deviatoric stress tensor $\boldsymbol{S}$, which is obtained from the Cauchy stress tensor $\boldsymbol{\sigma}$ by a linear transformation; m is an exponent which can be considered equal to, respectively, 6 for BCC and 8 for FCC materials [28] and $\bar{\sigma}$ is the equivalent stress. The linear transformation used to calculate the isotropic plastic equivalent (IPE) stress tensor S is

$$\mathbf{S} = \mathbf{L} : \boldsymbol{\sigma} \tag{2}$$

where $\mathbf{L}$ is the linear transformation tensor, defined for orthotropy [29] by

$$\mathbf{L} = \begin{bmatrix} (c_2+c_3)/3 & -c_3/3 & -c_2/3 & 0 & 0 & 0 \\ -c_3/3 & (c_3+c_1)/3 & -c_1/3 & 0 & 0 & 0 \\ -c_2/3 & -c_1/3 & (c_1+c_2)/3 & 0 & 0 & 0 \\ 0 & 0 & 0 & c_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & c_5 & 0 \\ 0 & 0 & 0 & 0 & 0 & c_6 \end{bmatrix} \tag{3}$$

where c_1, c_2, c_3, c_4, c_5 and c_6 are the parameters that describe the anisotropy. When all parameters c_i ($i = 1$ to 6) are equal to one and $m = 2$, the YLD91 criterion reduces to the von Mises yield criterion. The parameters to be identified in this model are c_1, c_2, c_3 and c_6. The parameters c_4 and c_5, the identification of which requires shear tests to be performed in the sheet thickness, are kept constant and equal to isotropic values ($c_4 = c_5 = 1$); this is because the experimental database does not involve such strain paths. As above mentioned, an exponent value of $m = 8$ is used [28], which is coherent with the behaviour of FCC materials such as aluminium alloys.

The yield surface is described by the equation:

$$\Phi = \bar{\sigma} - Y = 0 \tag{4}$$

where Y is the yield stress that takes as initial value Y_0. The yield stress evolution is given by the Voce law [23], defined as:

$$\dot{Y} = C_Y(Y_{\text{sat}} - Y)\dot{\bar{\varepsilon}}^p \tag{5}$$

where $\dot{\bar{\varepsilon}}^p$ is the equivalent plastic strain rate and C_Y and Y_{sat} are material parameters to be identified. This model is used in the simulation of materials whose behaviour presents saturated hardening.