Inverse analysis procedures for elastoplastic parameter identification using combined optimisation strategies

B Coelho[1], A Andrade-Campos[2] and J M P Martins[3]
Centre for Mechanical Technology and Automation (TEMA), Department of Mechanical Engineering
University of Aveiro
Aveiro, Portugal
[1] bcoelho@ua.pt, [2]gilac@ua.pt, [3]joao.martins52@ua.pt

***Abstract* — Ensuring accurate and efficient models for the representation of the elastoplastic behaviour of sheet metals is one of the main issues in manufacturing simulation processes. Nowadays, there are a few solid numerical methodologies for predicting the material parameters from full-field strain measurements using digital image correlation (DIC) techniques. External methods, such as the Finite Element Model Updating (FEMU), search for the parameter set that minimises the gap between the experimental and numerical observations. In these methods, a total separation between the experimental and the numerical data occurs. Equilibrium methods, such as the Virtual Fields Method (VFM), search for the parameter set that balances the internal and external work according to the principle of virtual work, where the internal work is calculated using the constitutive model applied to the experimental strain field [1-5]. Both described methods are still expensive and non-robust, which is closely related with the adopted single-stage optimisation strategies. Such optimisation strategies can undergo problems of initial solution's dependence, non-uniqueness of solution, local and premature convergence, physical constraints violation, etc. Therefore, the choice of an optimisation algorithm is not straightforward.**

The aim of this work is to implement and analyse advanced optimisation strategies with sequential, parallel and hybrid approaches in a parameter identification problem using both the VFM and the FEMU methods. The performance of a gradient least-squares (GLS) optimisation algorithm, a metaheuristic (MH) algorithm and their combination is compared. Moreover, the definition of the objective functions of both VFM and FEMU methods is discussed in the framework of optimisation.

Table 1, for instance, provides results of a parallel strategy that combines FEMU and VFM. In this strategy, the objective function is given by the sum of the weighted objective functions of each method (multi-objective approach).

Table 1: Results considering data with and without noise.

	No noise		Noise	
FEMU weight	**Objective Function**	**Parameters average error**	**Objective Function**	**Parameters average error**
0.0	**5.50E-07**	**0.707%**	**1.78E-03**	**42.994%**
0.2	**5.35E-06**	**0.355%**	**7.05E-03**	**9.936%**
0.5	**6.94E-06**	**0.207%**	**7.35E-03**	**-2.127%**
0.8	**4.06E-06**	**0.080%**	**6.48E-03**	**-6.341%**
1.0	**3.70E-02**	**17.243%**	**4.47E-03**	**-9.409%**

The parallel strategy presents significantly lower average errors in the identification of parameters when compared to the single VFM or FEMU approaches (FEMU weight equal to 0 or 1, respectively).

Keywords* — *calibration of constitutive models; metal plasticity; full-field measurments; finite element model updating; virtual fields method; gradient-based optimisation algorithm; metaheuristic optimisation algorithm.

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