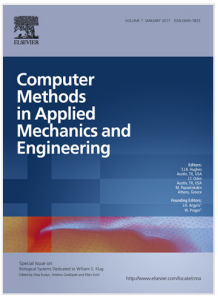
Accepted Manuscript



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Daniele Versino, Tonda Alberto, Curt A. Bronkhorst

PII: S0045-7825(16)31449-9
DOI: http://dx.doi.org/10.1016/j.cma.2017.02.016
Reference: CMA 11343

To appear in: *Comput. Methods Appl. Mech. Engrg.*

Received date: 28 October 2016
Revised date: 7 February 2017
Accepted date: 8 February 2017

Please cite this article as: D. Versino, T. Alberto, C.A. Bronkhorst, Data driven modeling of plastic deformation, *Comput. Methods Appl. Mech. Engrg.* (2017), http://dx.doi.org/10.1016/j.cma.2017.02.016

Data driven modeling of plastic deformation

Daniele Versino[a,*], Tonda Alberto[b,**], Curt A. Bronkhorst[a]

[a] *Theoretical Division, T-3, Los Alamos National Laboratory*
Los Alamos, New Mexico 87545, USA
[b] *UMR GMPA, AgroParisTech, INRA, Université Paris-Saclay*
1 av. Brétignières, 78850, Thiverval-Grignon, France

Abstract

In this paper the application of machine learning techniques for the development of constitutive material models is being investigated. A flow stress model, for strain rates ranging from 10^{-4} to 10^{12} (quasi-static to highly dynamic), and temperatures ranging from room temperature to over 1000 K, is obtained by beginning directly with experimental stress-strain data for Copper. An incrementally objective and fully implicit time integration scheme is employed to integrate the hypo-elastic constitutive model, which is then implemented into a finite element code for evaluation. Accuracy and performance of the flow stress models derived from symbolic regression are assessed by comparison to Taylor anvil impact data. The results obtained with the free-form constitutive material model are compared to well-established strength models such as the Preston-Tonks-Wallace (PTW) model and the Mechanical Threshold Stress (MTS) model. Preliminary results show candidate free-form models comparing well with data in regions of stress-strain space with sufficient experimental data, pointing to a potential means for both rapid prototyping in future model development, as well as the use of machine learning in capturing more data as a guide for more advanced model development.

Keywords: Strength models, high strain rate, J_2 plasticity, machine learning, symbolic regression, Taylor anvil impact

1. Introduction

Modeling materials is of extreme importance for a wide range of practical reasons: for example, since experiments are costly and time-consuming to perform, a mathematical model can provide fast predictions of material behavior, allowing experts to test new structures or solutions in an inexpensive way. Researchers in the past focused on the development of new phenomenological constitutive models by finding approximate expressions that described the physical phenomena underlying the observed macroscale behavior. These expressions usually depended on several empirical parameters that were computed, or calibrated, using experimental data. Stripped to the essential, material modeling at the macroscale level consists in finding the best fit (equation) for a set of experimental data, using observations at micro and macro scales. As models become more complex and advanced in their physical basis, however, there is a corresponding rise in the complexity of empirical expressions and increased difficulty in the parameter calibration. This complexity is eased through a focus on the development of more physically based models where quantities are well defined and can be evaluated independently.

From a different perspective, developing a material model at the macroscopic continuum scale can be seen as an optimization problem: for a given set of points in an n-dimensional space, find the functional (or set thereof) that is closest to the input points. The complexity of such an optimization problem is non–polynomial (NP–hard problem) [1]. If the form of the interpolating function is an *a priori*, the problem reduces to finding the parameter values that

*Daniele Versino, Tel: +1 505 667 2137.
**Alberto Tonda, Tel: +33 1 3081 4596.
Email addresses: daniele.versino@lanl.gov (Daniele Versino), alberto.tonda@grignon.inra.fr (Tonda Alberto)