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Improved Sensitivity Analysis in the Inverse Identification of the Parameters of a Nonlinear Material Model

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Abstract

During the inverse identification of the parameters of a nonlinear material model via an optimization algorithm, it is advantageous to utilize sensitivity analysis as a pre-processing tool to decrease the dimensions of the design vector by removing insignificant parameters. As regards the optimization and sensitivity analysis, a crucial aspect consists in the choice of the objective function. It is possible to derive special forms of objective functions for better understanding of the functionality of the given complex material model. The present article discusses three types of Python scripts that facilitate the calculation of different objective functions from the numerically and experimentally obtained load-displacement curves.

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Keywords: Sensitivity, optimisation, identification, nonlinear material model of concrete, Python.

1. Introduction

The numerical solution of structural design problems has been very popular for many years. The popularity, indicated in [1,2,3,4,5], results from both the good current knowledge of numerical methods and the fact that the numerical simulation of certain complex and atypical structural elements is less costly than the experimental testing of real specimens. The use of nonlinear material models of concrete to simulate the behavior of real structures is often complicated by unknown material parameters of the given material model. The relatively high number of such parameters is a consequence of the complexity of the behavior of concrete. One of the basic problems which arise

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when formulating a material model for concrete lies in the different responses of the material to tensile and compressive load [6]. However, there are also other phenomena that complicate the derivation of the correct constitutive law, e.g. the gradual decrease in the stiffness of concrete due to cracks, irreversible deformations, and volumetric expansions [7]. These effects have led to the development of a wide range of material models based on different assumptions. Due to these problems, a group of models exploits the assumptions of the pure theory of plasticity, a discipline allowing us to describe different behaviors in tension and compression and also inelastic irreversible deformations. Another group of material models of concrete uses damage theory, which is applicable for the description of the occurrence and development of cracks. As neither of these theories is suitable for independent use, other material models are available that combine the theory of plasticity with damage theory [8] and other approaches formulated within nonlinear mechanics. The last mentioned concept is represented by multiPlas [9], a commercial database of elasto-plastic material models, which was developed to support nonlinear simulations in ANSYS [10]. The method based on the combination of multiple theories in one computational law produces a wide range of unknown mechanico-physical and fracture-mechanical material parameters. In this situation, it is possible to make advantageous use of experimentally obtained load-displacement curves measured during the testing of test specimens fabricated from selected materials and to reverse identify the required parameters via inverse identification.

The inverse identification of these unknown parameters can be performed using artificial neural networks, as described by Novak and Lehky [11], or by means of the optimization algorithm shown in [12], while the classical usage of the optimization of structural design problems is described by Fedorik et al. [13]. The principle of optimization-based identification consists in minimizing the difference between experimentally and numerically obtained load-displacement curves. However, there emerges the problem of how to formulate this difference as precisely as possible because the choice of a suitable objective function is crucial for achieving the optimum. One possible way is to employ the root-mean-squared error, often utilized to evaluate the accuracy of mathematical models in economics or weather forecasting [14]. The need of the right objective function also applies to sensitivity analysis, which can be used as a pre-processing tool during inverse identification. The main purpose of sensitivity analysis is to identify how the output data uncertainties are influenced by the variability of the input data [15] and, on this basis, to find the right reduction of the design vector dimension. A wide variety of options are available for special derivation of the objective function to be used in detecting the dependencies that can be hidden when one objective function is used.

The present article discusses three types of Python-programmed scripts enabling the calculation of partial objective functions. The potential of this approach lies in the opportunity to reveal the sensitivity of some special material parameters that occur in special types of loading.

Nomenclature

d	Vertical displacement measured during testing a concrete specimen at the mid span on the lower surface
E	Young's modulus of elasticity
f_t	Ultimate tensile strength
f_c	Ultimate compressive strength
G_{fc},	Specific fracture energy in compression
G_{ft}	Specific fracture energy in tension
k	Ratio between biaxial compressive strength and uniaxial compressive strength
L	Load measured on the testing machine
n	Number of observations (samples)
RMSE	Root-mean-squared error measure
r_s	Spearman-rank correlation coefficient
X_i	Input variable
Y_i	Output variable
y_i^*	Value of the force calculated within the framework of the numerical simulation
y_i	Value of the force gained from the experimental L-d curve
δ_i	Difference between the ranks of each observation
ε_{ml}	Plastic strain corresponding to the maximum load