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IDENTIFICATION OF COMPUTATIONAL MODEL PARAMETERS USING STOCHASTIC SIMULATIONS AND ARTIFICIAL NEURAL NETWORKS

Summary

Inverse problems appear in many engineering disciplines in similar forms. The solutions are identical in principle, but are presented under different names (e.g. inverse analysis, identification, model updating). The goal is to identify parameters of a computational model of a system (e.g. a structure), based on the observation of its response. Focusing on problems of engineering computational mechanics solved mainly by the finite element method (FEM), the basic types of tasks can be mentioned as follows. For better orientation the symbols IP (identification parameters) and MD (measured data) will be used.

Gaining information on the loads acting on a structure, based on the observation of the response (e.g. deformation, stresses), represents a classical identification problem. Maincon (2004) suggests a procedure of the inverse finite element method (iFEM), formulated and applied successfully mainly for linear problems of computational mechanics. Problem classification: IP = load, MD = response in selected points.

EAn early detection of the level and/or localization of the damage using non destructive methods is getting more and more important nowadays also due to the increasing maintenance cost. A well known technique is a dynamic experiment. Using vibration measurements, the natural frequencies and mode shapes are obtained. The real dynamic behavior is compared with a FEM computational model. For application in bridge engineering, approaches, called “model updating”, are developed. Problem classification: IP = material model parameters, MD = frequencies and mode shapes based on a dynamic experiment.

A strong interest has developed to formulate inverse methods to determine the quasi-brittle fracture behavior of concrete. There are basically two groups of inverse analysis techniques: (1) those that use the complete load-displacement curve of one specimen size and shape; (2) those that use the peak loads of specimens of various sizes and shapes capturing the size effect phenomenon. In case of identification of material parameters using non destructive testing (monitoring system on real structures) the data are obtained only from certain load-levels because the whole load-deflection curve is not available. Problem classification: IP = material model parameters, MD = load-deflection curve or part of it.

Methodological and conceptual approach

For the purposes of inverse analysis the methodology based on coupling of stratified simulation of the Monte Carlo type and the artificial neural network was worked out. The emphasis is on: (1) the efficiency of stochastic training of the neural network using a small number of simulations based on stochastic techniques Latin Hypercube Sampling with the possibility of taking the correlation among parameters into account; (2) the multipurpose character of the methodology relatively easy to apply.

In the presented identification technique the identification parameters play the role of basic random variables with a scatter reflecting the physical range of possible values. The simulations of Latin Hypercube Sampling will serve for training of a suitable neural network. Once the network is trained it represents an approximation consequently utilized in an opposite way: For the given experimental data to provide the best possible set of model parameters. The whole procedure can be itemized as follows (figure):

1) The computational model has to be first developed using the appropriate computational model of the given problem. The model has to be heuristically “tuned” using model parameters (IP); the initial calculation uses a set of initial material model parameters leading to a rough agreement with experimentally measured data (MD). This

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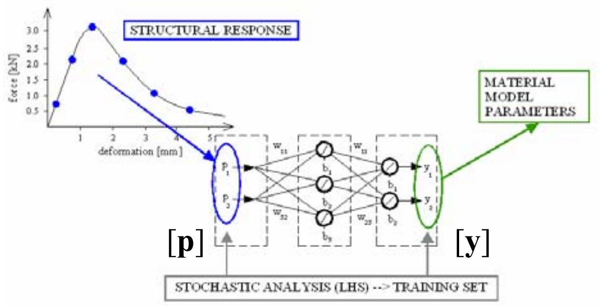
preliminary step is based on rough knowledge of some model parameters and engineering estimation. “Tuning” is done heuristically using a



few iterations in such a way that numerical results are not so far away from MD.

2) IP of the material model are considered as random variables described by probability distributions, rectangular distribution is a “natural choice” as the lower and upper limits represent the bounded range of physical existence. But also other distributions can be used, e.g. the Gaussian one. IP are simulated randomly based on the Monte Carlo type simulation, the small-sample simulation LHS is recommended. The results are random realizations of IP (vector **y). ** A statistical correlation between some parameters can be taken into account (if known then it can help the inverse analysis in the consequent stochastic training).

3) A multiple calculation of the deterministic computational model using random realizations of IP **y** is performed, a statistical set of the virtual response **p** is obtained.

4) Random realizations **y** and the random response from the computational model **p** serve as the basis for the training of an appropriate neural network. This key point of the whole procedure is illustratively sketched in the figure (for FEM model response in the form of nonlinear load-deflection curve including a post-peak behavior).

5) After the training the neural network is ready to fulfil the opposite task: To select the best parameters IP in order that the computation will result in the best agreement with MD. This is performed by means of the simulation of the network using MD as an input. It results in a set of parameters $\mathbf{y}_{opt}$.

6) The last step is the results verification – calculation of the computational model using parameters $\mathbf{y}_{opt}$. A comparison with MD will show to what extent the inverse analysis was successful.

The basic element of the whole procedure is the generation of the training set (a certain number of random simulations), which can be time consuming (e.g. in a nonlinear FEM analysis). The utilization of LHS appeared to be very useful, as the whole multi-dimensional space of IP is covered by a relatively small number of simulations.

Research results

Methodology of the inverse analysis was verified by several applications, e.g. identification of material parameters of high-performance concrete for railway sleepers (Lehký & Novák, 2004), glass-fiber reinforced composites (Keršner et al., 2005), cement composites under high temperature loading (Matesová & Lehký, 2005), modeling of the shear wall failure mode (Červenka et al., 2005), or identification of statistical parameters of reinforced concrete frame structure (Lehký & Novák, 2005).

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