

Dilatometric tests combined with computer simulations and parameter identification for in-depth diagnostic analysis of concrete dams

A. Zirpoli, G. Maier, G. Novati & T. Garbowski

Dept. of Structural Engineering, Politecnico di Milano, Milan, Italy

ABSTRACT: Diagnostic analysis of dams means here assessment of possible structural damages (due to, e.g., alkali-silica reaction in concrete). Such damages may be primarily self-equilibrated stresses due to material expansion, elastic stiffness degradation, decrease of compressive and tensile strength, and of fracture energy. The procedure presented in this paper is intended to perform such diagnosis deep inside the concrete dam and is based on “ad hoc” devised substantially novel mechanical experiments, on their finite element modelling and on deterministic parameter identification through the minimization of the discrepancy norm between measured quantities and their counterparts computed as functions of the sought parameters.

1 PRELIMINARY REMARKS

In present dam engineering the assessment of possibly deteriorated material properties and of the stress state, both in dam concrete and in foundation rocks, is necessary in order to compute the present safety factors with respect to various kinds of possible failures. Typical structural problems in concrete dam engineering are dealt with e.g. in Pedro (1999) and Bourdarot et al. (1994).

As for diagnostic analysis of possible damages in concrete dams (due to alkali-silica reactions and/or extreme loads like exceptional floods and earthquakes), the following methodological classification can provide a concise overview, see e.g. Maier et al. (2004), Fedele et al. (2006):

(a) overall dynamic excitation and accelerometric measurements; (b) hydrostatical loading due to seasonal variations of reservoir level and measurement of consequent displacements by pendula, collimators, and, recently, radar; (c) same as at (b), but with “fast” hydrostatical loading performed by “ad hoc” changes of the reservoir level; (d) local, traditional flat-jack tests on dam surface and extensimetric or, in the future, “digital image correlation” measurements; (e) traditional “overcoring” for damage and stress assessment in-depth.

Overall diagnosis procedures are clearly limited to the assessment of elastic stiffness distribution; the static approaches provide more data if radar is employed and are especially inexpensive if seasonal. Local tests are needed in order to assess fairly accurately stress states and inelastic material properties.

In this paper a new methodology is proposed in order to perform diagnostic analyses locally, in-depth and in a relatively inexpensive and non-destructive fashion. The diagnostic method here presented, inspired by the traditional overcoring technique but substantially different from it, is centered on inverse analyses and is articulated in the operative phases specified in the subsequent Section. The in-depth material characterization has been, since several decades, a research subject, particularly in rock mechanics, and a widely employed practice in geotechnical engineering. Wittke (1990) and Sjöberg & Klasson (2003) can be regarded as representative references to the relevant vast literature.

2 OUTLINE OF THE EXPERIMENTAL PROCEDURE AND RELATED PARAMETER IDENTIFICATION

The operative phases of the proposed diagnostic method are listed below and schematically illustrated in Figure 1.

- a. A hole is drilled in the dam (Figure 1a).
- b. A device called “dilatometer” is inserted in it. The dilatometer basically consists of two sleeves equipped with radial displacement gouges and, between them, of two movable steel “arches” (Figure 1b).
- c. The drilling goes ahead, making the hole longer, while the gouges measure the displacements due

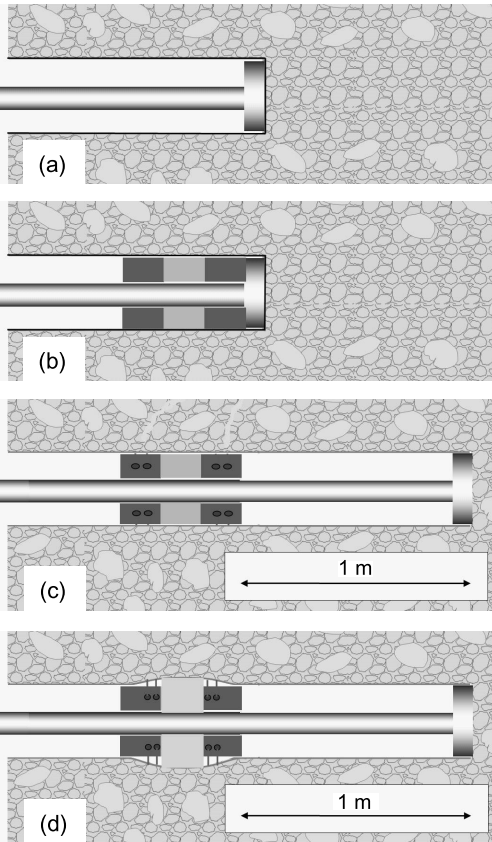


Figure 1. Operative phases of the proposed procedure.

- to the stress state modification caused by the excavation advancement (Figure 1c).
- d. The two steel “arches”, governed by two small hydraulic jacks (fed by a volumetric external pump), apply two growing radial forces (equal magnitude, opposite directions) on the hole’s wall. The gauges measure the displacements, first generated in the linear elastic range (Figure 1d).
 - e. The same operations of phase (d) are performed, but this time the elastic limit is overcome by increasing the jack pressure. The pump feeds the jacks through small pipes placed into the tube which supports the dilatometer and contains the drill shaft.
 - f. A laptop containing an artificial neural network, trained through computer simulations of the mechanical tests, collects the signals from the gauges, digitalizes them and performs inverse analyses which provide the sought parameters, in the following sequence: (i) Young modulus and Poisson coefficient (under the hypothesis of isotropic material), on the basis of the experimental data collected during phase (d); (ii) the stresses, two normal

and one tangential, in the plane orthogonal to the hole axis, on the basis of the data coming from phase (c); (iii) the parameters governing a plastic constitutive model and/or a quasi-brittle fracture model (e.g.: the three parameters of Drucker-Prager model and/or the two of the simplest cohesive crack model).

- g. The drilling goes ahead and the sequence of the above outlined phases is repeated at a new position and direction in the dam.

For the repeated inexpensive “in situ” use of the equipment, accurate nonlinear finite element modeling is needed, but once-for-all only, in order to generate by the “forward operators” a suitable number of “patterns” for the “training” and the “testing” of the neural networks to be employed on site.

The above outline of the proposed diagnostic procedure for concrete dams can be clarified and motivated by the following remarks.

- α. No specimen is extracted from the borehole to be tested in laboratory, at a basic difference from traditional core drilling procedures. Since dam concrete is inhomogeneous with aggregate sizes larger in average than in the usual concrete employed with steel reinforcement for buildings and bridges, carrots should be rather large and, hence, damaging (say, with a diameter an order of magnitude larger than expected maximal aggregates) in order to avoid misleading inaccurate experimental data.
- β. Displacements, not strains, are measured. In fact, strain gauges usually adopted for overcoring techniques would be unsuitable for concrete, since, clearly, strains are sensitive to local material properties (quite different from mortar to aggregate), whereas displacements reflect, in a sense, average properties, namely the large-scale material properties of structural engineering interest.
- γ. Inelastic properties are the main targets of the proposed procedure, since so far such properties are not assessed “in situ” and in-depth according to the present practice of concrete dam engineering.
- δ. The instrumented equipment envisaged herein is not available at present on the market, but it is clearly possible (and relatively inexpensive) to produce it by the present technology, even if with major changes with respect to the current practice. Therefore, the preliminary validation of the method presented in what follows rests on a pseudo-experimental approach, namely measurable data are computed by means of simulations of foreseen experiments through a finite element model, starting from reasonably assumed values of the sought parameters; then these values are compared to those arrived at by the inverse analyses, and a suitable discrepancy function is

minimized, taking those parameters as mathematical optimization variables. Clearly, recourse to pseudo-experimental data for methodological validation implies that the systematic (not random) modeling errors are not considered.

- e. The proposed diagnostic technique is dealt with at a preliminary design stage. To its further improvement “sensitivity analyses” are useful, namely numerical tests apt to make sure that the quantities (here displacements) to be measured as “effects” are sufficiently influenced by the sought parameters acting as “causes”, see e.g. Kleiber et al. (1997). Some analyses of this kind are presented within the computational exercises summarized in Section 3.

3 COMPUTATIONAL VALIDATION OF THE DIAGNOSTIC TECHNIQUE

The finite element model built up for the computer simulation of tests is visualized in Figure 2 and its main features are specified below.

- a. In order to mitigate the computing efforts, the following simplifying assumptions are adopted for the subsequent comparative numerical tests: (i) material isotropy (which is not always acceptable for dam concrete, particularly for rolled compacted concrete (RCC)), in view of the frequently consequent non-negligible orthotropy with horizontal isotropy only; (ii) symmetries with respect to the vertical and horizontal planes through the hole axis; (iii) the three-dimensional domain of the problem exhibits typical lengths which are 10 times longer than the hole radius, so that the boundary can be regarded as unaffected by the mechanical events produced by the tests; (iv) rigid constraints are imposed on the remote boundary (statical condensation or infinite elements will be employed in future investigations); (v) the longitudinal direction represents a principal direction for the stress state with vanishing normal stress; (vi) the original stress field before testing is uniform and generated at Gauss points; (vii) the drilling of the hole is simulated by removing radial restraints placed along the hole boundary (such restraints being active when the initial “in situ” stresses are enforced at the Gauss points).
- b. The traditional finite element model qualitatively described above, can quantitatively be specified as follows: 57781 tetrahedral elements with linear interpolations for displacements; 36111 degrees of freedom; commercial code Abaqus (version 6.6).
- c. The constitutive models adopted herein for a first validation are the following classical ones, see Figure 3 and, e.g., Jirasek & Bažant (2001) or

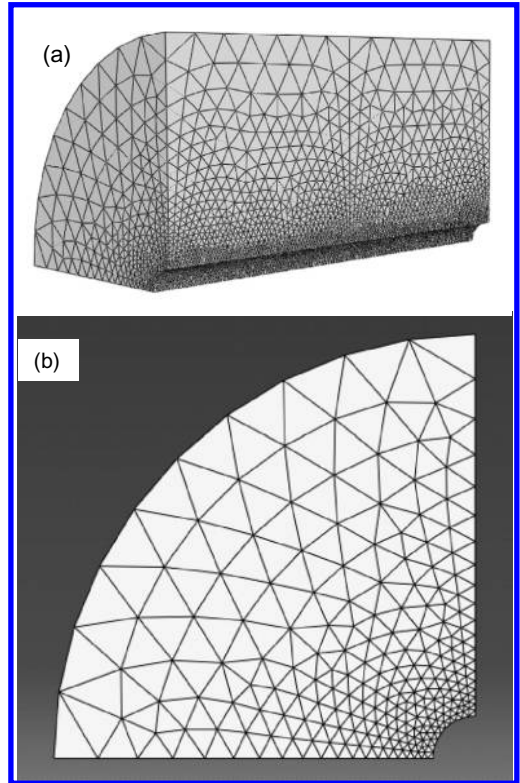


Figure 2. Finite element mesh adopted for the computational validation of the method; (a) 3D view, (b) mesh in the transversal plane.

Kaliszky (1989): linear elasticity with 2 parameters, of which only the Young modulus E is to identify, while Poisson ratio is assumed as $\nu = 0.2$; Drucker-Prager perfect plasticity (3 parameters: cohesion d , hydrostatic compressive strength p_b and internal friction angle β), improved by a “cap” (1 parameter: cap eccentricity R) in view of expected stress states with dominant compression.

Reference values reasonably expected in dam concrete are attributed to the material parameters and stresses to identify, namely: $E = 28000$ MPa, hydrostatic compressive strength $P_b = 35$ MPa, cohesion $d = 3.5$ MPa, friction angle $\beta = 51^\circ$, and cap eccentricity $R = 0.65$; pre-existing horizontal and vertical principal stresses: $\sigma_H = 5$ MPa and $\sigma_V = 10$ MPa, respectively, both compressions. The other two parameters required by the model, i.e. the transition surface radius (α) and the initial plastic volumetric deformation, were considered respectively equal to 0.6 and to 0.

Figure 4 shows some plots of imposed force vs measured displacement of the “arches” with different values attributed to the parameter p_b which, together

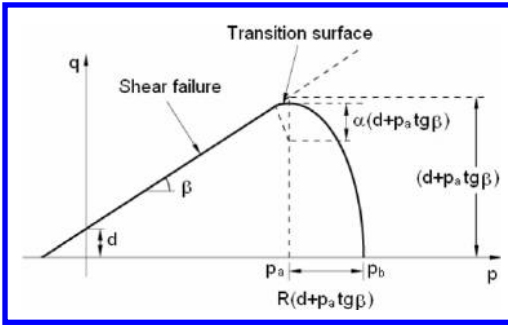


Figure 3. Drucker-Prager model with “cap” and relevant parameters d , p_b , β and R are to identify.

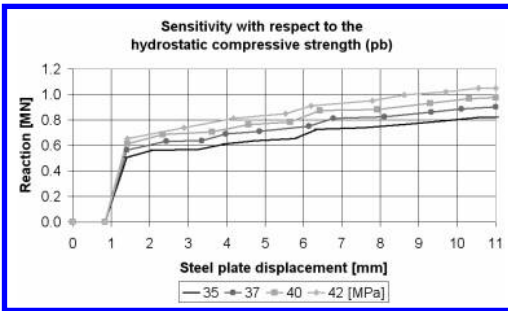


Figure 4. Force vs displacement concerning the “arches” for various values for parameter p_b .

with R , governs the “cap” on Drucker-Prager model. Plots like these visualize the sensitivity of measurable quantities with respect to sought parameters, as a simplified alternative to the sensitivity analysis in terms of derivatives (Kleiber et al. 1997).

Using such values and the finite element model shown in Figure 2, the radial displacement of the arch is computed (up to 10 mm) as a function of the force generated on it by the small jack. Such computations are repeated and their results plotted in Figure 4 after having each time assigned a value indicated in the figure to one of the material parameters to identify. The above sensitivity analyses show that the measurements planned by means of the envisaged instruments are likely to be adequate for the identification of the sought parameters.

Present parameter identification by a deterministic batch (non sequential) approach to inverse analysis, means solution of a generally non-convex mathematical programming problem. Such problems are tackled here first, to methodological validation purposes, by the “Trust Region” iterative algorithm. This algorithm is a special case of sequential quadratic programming method: it implies at each step finite difference evaluation of the gradient only (“first order algorithm”) and solution of a quadratic program in two variables, see

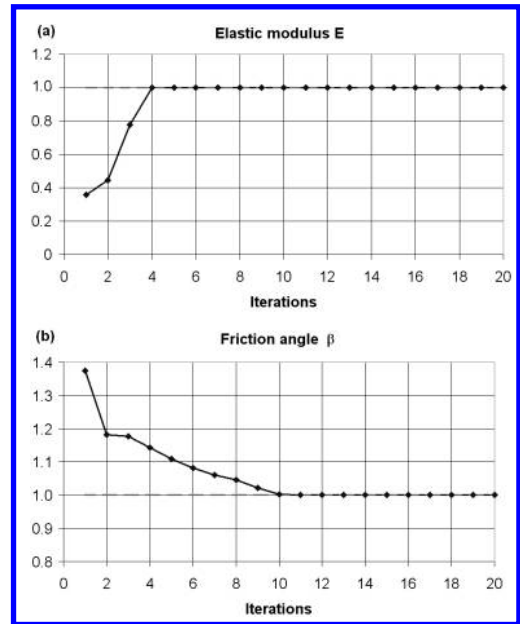


Figure 5. Convergence of the identification process: (a) normalized elastic modulus E ; (b) normalized internal friction angle β .

e.g. Coleman & Li (1996). The discrepancy function to minimize is here defined as the Eulerian quadratic norm of the differences between pseudo-experimental data and their computed counterparts. In fact, the inverse of the covariance matrix of measurement random errors can be reasonably assumed as equal to the identity matrix, since the instruments are all equal and correlation is negligible.

The convergence processes resulting from some of the exercises performed so far in this study, are visualized in the following figures: elastic modulus and friction angle (see Figure 5a and 5b), hydrostatic compressive strength, cohesion and cap eccentricity (see Figure 6a, 6b and 6c), horizontal and vertical normal stresses (see Figure 7a and 7b).

All parameters are “normalized” with respect to their (above specified) values assumed in order to generate by “direct analyses” the pseudo-experimental data employed as input of the inverse analyses. The chosen initializations are rather distant from the values attributed to the parameters. This circumstance helps to conjecture the absence of local minima of the discrepancy function, a conjecture also supported by visual maps of the discrepancy functions here omitted for brevity.

The average computing time required by the above outlined inverse analyses amounts to 35 hours with a computer characterized by a 2GB RAM and a 2.4 GHz velocity. Clearly, this circumstance represents a significant burden in terms of cost and time, a burden

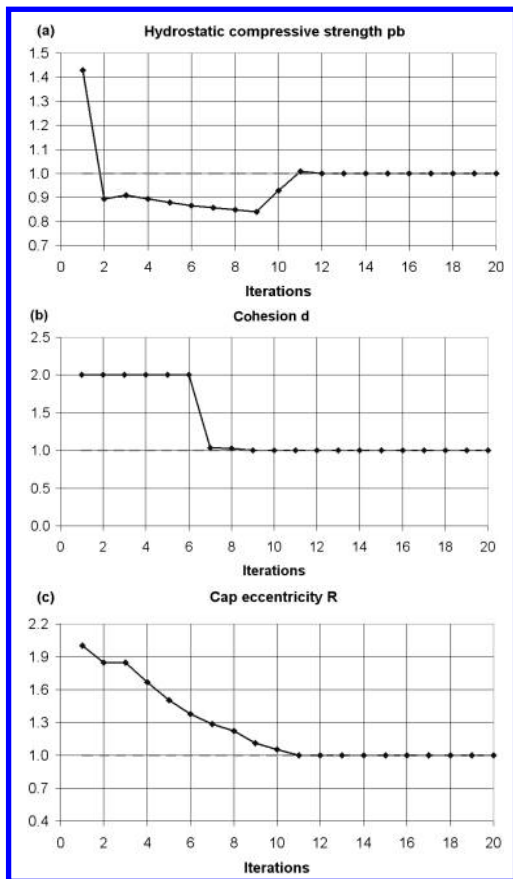


Figure 6. Convergence of the identification processes: (a) hydrostatic compressive strength p_b , (b) cohesion d , (c) cap eccentricity R .

which can at present be avoided by recourse to soft computing, specifically here to artificial neural networks (ANNs), see Haykin (1999). Such practically important feature of the diagnostic method proposed herein can be outlined as follows (details and numerical results will be presented in the full paper in preparation).

The outline holds for each one of the three parameter identifications described in what precedes.

α . The set of experimental data which should represent the input of the inverse analysis is approximated in order to achieve a balance between input and output of the ANN (the output consisting of one or two parameters in the present context, of three or four at most in future applications). Such approximation is achieved by polynomials here

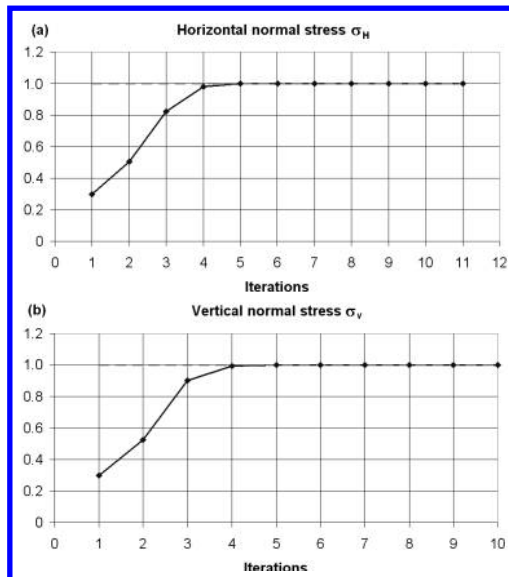


Figure 7. Convergence of the identification processes: (a) horizontal normal stress σ_H , (b) vertical normal stress σ_v .

(cf. e.g. Waszczyszyn (1999)), by proper orthogonal decomposition (probably better) in future developments (see e.g. Ostrowski et al. (2005)).

- β . The ANN “architecture” is designed according to the criteria expounded in the literature (see e.g. Waszczyszyn (1999)) primarily in order to avoid “overfitting” (here specifically two “hidden layers”, each one with 5 active neurons).
- γ . A grid of points is selected on a reasonably bounded domain in the space of the sought parameters and for each point the corresponding vector of measurable quantities is computed by direct analysis (through the finite element model) and approximated as hinted at phase (α).
- δ . A subset (here 500) of the patterns generated in the preceding phase, after perturbation by a suitable random “noise” (here with uniform probability density over $\pm 5\%$), is employed for the ANN “training”, namely for the identification of “weights” and “biases” of active neurons by means of a traditional “back propagation” algorithm. The remaining patterns (here 200) are used for the ANN “testing”.

4 CLOSING REMARKS

The diagnostic technique briefly described in what precedes exhibits several substantial novelties, potentially advantageous in engineering practice. The most promising features arise from accurate once-for-all

computer simulations of the tests and on-site use of artificial neural networks for inverse analyses in situ. Investigations now in progress are intended to further improve the efficiency of the method and to increase the number of identifiable parameters, particularly by means of the following prospects: sharp indenters, employed after the arches, in order to provoke fracture in an easier and more intensive fashion apt to accurate assessment of fracture properties (fracture energy “in primis”); optimized geometries of the dilatometer positions and of the whole equipment; repeated tests after 90 degree rotation of the instrument in order to increase the available experimental data.

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