Damage Identification and Uncertainties in Coupled Non-Linear Thermo-Hydro-Mechanical Problems Applied to Masonry Dams

Long Nguyen-Tuan[1)], Tom Lahmer[1)], Carsten Könke[1)] and Volker Bettzieche[2)]
[1)] *Institute of Structural Mechanics – Bauhaus-Universität Weimar, Marienstrasse 15, 99423 Weimar, Germany,*
{long.nguyen.tuan, tom.lahmer and carsten.koenke}@uni-weimar.de
[2)] *Department of Dam Maintenance and Geotechnics, Ruhrverband, Germany,*
vbe@ruhrverband.de

Abstract: In this paper, we introduce a method to identify a damage zone and the material properties at the damage zone by means of inverse analysis based on a series of measurement data such as transient displacements, temperatures and water pressures. The inverse problem is solved iteratively by the Particle Swarm Optimization method. The uncertainty of the measurement data may propagate to the uncertainty in the identification of the damage zone. This paper considers the uncertainty of the measurements by assuming different noise levels of the measurements. The uncertainty of the damage zone can be quantified by its probability distribution.

Keywords: damage identification, masonry dam, optimization, uncertainty quantification

1. Introduction

After more than one hundred years in use, material properties of the masonry dam bodies are changed. The deterioration of the material properties is supposed because of ageing, weathering and chemical effects. Consequently, there could appear some zones or cracks, where the properties of the material (e.g. stiffness, permeability and thermal conductivity) have a big change. It is useful and economic that the damage zone can be identified based on the present measurement data, which are obtained via the devices which are permanently installed in the dam.

Ordinarily, masonry dams have to bear two major loads: water pressure and self-weight load. Besides that the temperature inside the dam structure varies according to the water levels and air temperatures. This causes stresses within the structure and deformation of the dam. These behaviours have been monitored in terms of temporal displacement, water pressure, and temperature. According to the measurement in (Bettzieche, 2004), the effect of temperature on the deformation of the masonry dam is significant. Therefore, thermal conduction, water transport and force - deformation relations have to be considered when performing numerical simulations of the dam (Nguyen-Tuan et al., 2015).

The damage can be identified based on statistics and optimization against the experimental data such as reduction of natural frequencies (Wang and He, 2007) or monitoring of displacements with radar (Ardito and Cocchetti, 2006). The damage zone of the dam has been also identified using the inverse problem based on a hydro-mechanical model (Lahmer, 2010). It is to note that the

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reliability of the solution of the inverse problem depends on the accuracy of the measurements, the variety of the measurements and the variety of loading conditions. The variety of the measurements is determined by the distribution of the measurement points and the type of measurements (e.g. displacement, water pressure, seepage of water and temperature). In this paper, we introduce a method to identify the damage zone by means of inverse analysis based on a series of measurement data such as transient displacements, temperatures and water pressures. The inverse problem is solved iteratively by the Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995). The uncertainties of the measurement data may propagate to the uncertainty in the identification of the damage zone. This paper considers the uncertainties of the measurements by assuming different noise realizations in the data and the uncertainties of the damage zone can be quantified by its probability distribution.

2. Methodology

2.1. Formulation of inverse analysis

The forward operator (F), which maps the input model parameters of the damage zone to the responses at the finite sub-domains or boundaries (i.e displacement u, water pressure P_l and temperature T), is

$$\begin{aligned} F &: X \to Y \\ \boldsymbol{p} &\mapsto (u, P_l, T), \end{aligned} \tag{1}$$

where X denotes the parameter space, Y denotes the space of responses. The responses at the sub-domains Γ is denoted by a set of responses e.g. $\boldsymbol{y}(t) = y(u(t), P_l(t), T(t))$, where t is the time, u is the displacement, P_l is the liquid pressure and T is the temperature. The measurements of the responses are generally distorted by a certain amount of noise. These measurements with noise are denoted by $\boldsymbol{y}^{\varepsilon}$. The $\boldsymbol{\varepsilon}$ is introduced as a set of random noise in the measurements, i.e.

$$\boldsymbol{y}^{\varepsilon}(t) = \boldsymbol{y}(t) + \boldsymbol{\varepsilon}(t). \tag{2}$$

Assuming that a finite element model is used as forward operator, which maps a model with damage zone to the model responses accurately, the inverse problem with given measured data is defined by

$$F(\boldsymbol{p}) = \boldsymbol{y}^{\varepsilon}(t). \tag{3}$$

In the indirect method of inverse analysis, the parameters $\boldsymbol{p}$ are estimated by minimising a norm of the difference between the measured responses ($\boldsymbol{y}^{\varepsilon}$) and the model responses ($F(\boldsymbol{p})$). The norm is known as 'objective function'. The optimization algorithms drive an objective function in a way to find the minimum value of the objective function by changing the input parameters systematically. The questions of the inverse problem are to define the parameters as variables for the forward model, to define the objective function and to establish a suitable iterative algorithm for optimizing the objective function.

2.2. Objective function

Let $\boldsymbol{y}^{\varepsilon}$ be a set of measured data from an experiment and $\boldsymbol{y}^{c}$ be a set of obtained data by numerical simulation depending on a vector of model parameters $\boldsymbol{p} = \{p_1, p_2, ..., p_J\}$. The difference between the calculated and measured values defines the residual

$$f_{tmd}(\boldsymbol{p}) = y^{\varepsilon}_{tmd} - y^{c}_{tmd}. \tag{4}$$

It is defined that $t = 1, 2, ..., T_t$, where T_t is the number of measured data according to time, $m = 1, 2, ..., M$, where M is the number of selected points for observation, $d = 1, 2, ..., D$ is the number of serial measurements, for instance temperature, degree of saturation, or stress in one location and ω_{tmd} is the weighting factor for each measurement, a function of the model parameters is expressed as a normalized weighted sum of the squared errors

$$f_d^{MAE}(\boldsymbol{p}) = \sqrt{\sum_{t=1}^{T_t} \sum_{m=1}^{M} \frac{[f_{tmd}(\boldsymbol{p})]^2 \omega_{tmd}}{\sum_{t=1}^{T_t} \sum_{m=1}^{M} [y^{\varepsilon}_{tmd}]^2}}\ , \tag{5}$$

where values of ω_{tmd} depend on the importance and reliability of the analysed data. In Eq. (5), it is assumed that $\sum_{t=1}^{T_t} \sum_{m=1}^{M} [y^{\varepsilon}_{tmd}]^2$ is larger than zero.

Finally, considering the multi-field data, such as D different serial measurements, the objective function is defined as

$$f(\boldsymbol{p}) = \frac{1}{D} \sum_{d=1}^{D} f_d^{MAE}(\boldsymbol{p}) \omega_d\ , \tag{6}$$

where ω_d is the weighting factor for each serial measurement.

In special cases, when the y^{ε} cannot be measured at each point, i.e. the flux of water out of the dam, the common method to do so is to collect the amount of water on finite areas. Figure 2 illustrates the water collection along the downstream side. The water fluxes at the areas $a-b$, $b-c$, $c-d$, $d-e$ and $e-f$ are collected at the collecting point a, b, c, d and e respectively. Therefore, in the numerical simulation we have to integrate the water in each domain ($a-b$, $b-c$, $c-d$, $d-e$ and $e-f$) in order to compare with the measurement data. For instance, water collected Q_o at a collecting point is

$$Q_o = \int_a^b q_o \mathrm{d}l = \int_a^b [q_x \cos(\theta) + q_y \sin(\theta)]\, \mathrm{d}l, \tag{7}$$

where q_o is the flux of water out of line a-b at position l. The direction of the flow is perpendicular with the boundary plain, therefore, q_o is converted from flux flowing x axis and flux following y axis, see Fig 1. Here, θ denotes the angle between boundary line and vertical axis.

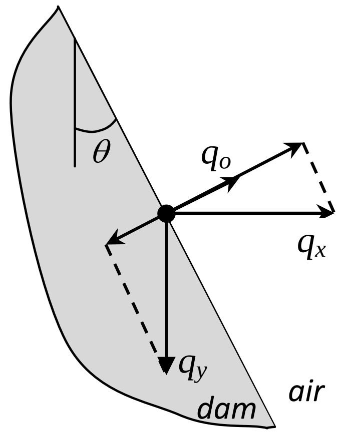

Figure 1. Axis translation of the out flow of water.

2.3. Parameterization of the forward problem

The parameters of the forward problem include a set of parameters for the initial materials (structures and subsoils), a set of parameters for the damage material, a set of parameters defining the geometry of the initial forward problem and a set of parameters defining the geometry of the damage zone. In this paper, we define the sets of parameters for the initial materials and the set of parameters defining the geometry of the initial forward problem as the constants. The set of parameters defining the geometry of the damage zone is considered the unknowns in the inverse problem. The geometry of damage zone is diverse. The complex geometry could lead to the complex function with many parameters, which could slow down the convergence of the objective function. It is acceptable if the damage zone can be quantified approximately by less number of parameters. In this paper, the geometry of the damage geometry is defined by a moving elliptic shape. The material parameters of the damage zone are also considered the unknowns. Therefore, the damage zone can be defined as follows,

$$g(\boldsymbol{p}) = g(\boldsymbol{p}_g, \boldsymbol{p}_m) \tag{8}$$

where $\boldsymbol{p}_g$ is the vector defining the geometry of the damage, $\boldsymbol{p}_g = (a, b, x_c, y_c, \alpha)$, in which a is the major radius, b is the minor radius, (x_c, y_c) are the center coordinates in the x, y plain, α the rotation angle of the major diameter. The elements inside this ellipse are defined as damage material. The example of the damage zone in the dam body is presented in Figure 2, the white elements represent the damage zone, which are bounded by the function $g(\boldsymbol{p}_g)$.

The vector $\boldsymbol{p}_m$ includes model parameters defining the behaviour of the material at the damage zone, $\boldsymbol{p}_m = (E, k_o, \lambda)$, in which E is the elastic modulus, k_o is the intrinsic permeability, λ is the thermal conductivity. The deterioration of the material properties at the damage zone has close correlation with the porosity. The change of porosity effects explicitly the elastic modulus, the permeability and the thermal conductivity. Therefore, the relations between E, k_o and λ are described in the constitutive models. With the change of porosity, these parameters will change, accordingly. Consequently, the number of unknown parameters reduces.

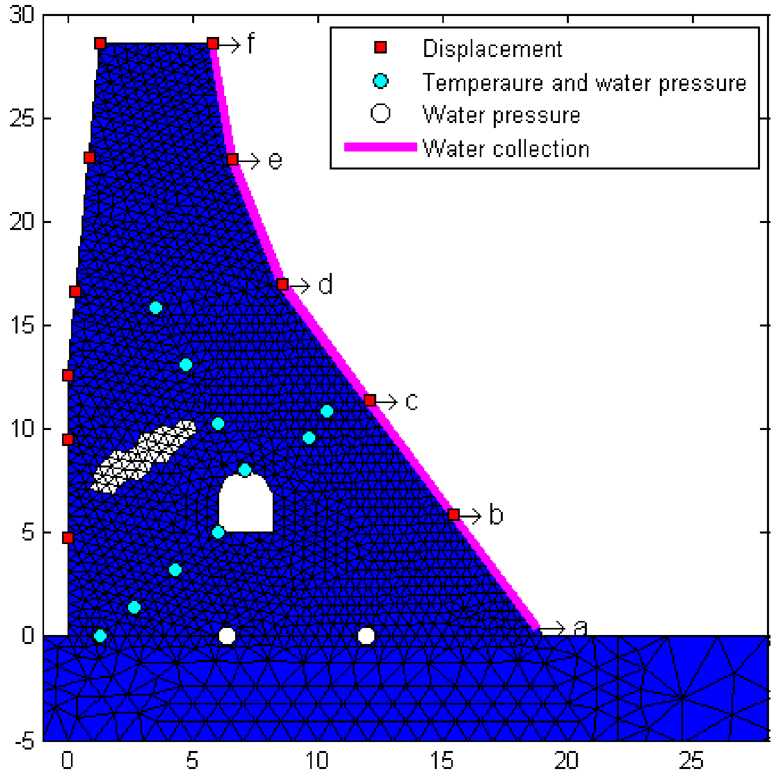

Figure 2. Geometry, assumed damage zone and measurement locations.

2.4. Optimization method

Particle swarm optimisation works basically by considering a population (called a "swarm") of candidate solutions of the optimisation problem (called particles). These particles are moved around in the search space according to several simple laws. The movements of the particles are guided by their own best known position in the search space as well as the entire swarm's best known position. Translating this to parameter identification problems, we consider a collection (swarm) of parameter vectors. Now, the entries in the vectors are repeatedly updated by combining local and global information about the values of the objective functions for the different parameter vectors. When better vectors are discovered, they will determine the further updates of the parameters. This process is repeated iteratively and by doing so, it is expected that a satisfactory solution of the calibration problem will eventually be discovered with high probability.

2.5. Uncertainties in damage identification

The sources of uncertainties in identification of the damage are of different types, for instance, the inhomogeneous material, the accuracy of the model, the accuracy of the measurements and the uncertainty of the optimization algorithm. This paper firstly intends to quantify the uncertainties caused by the accuracy of the measurements and the uncertainty of the optimization algorithm. By changing the amount of noise $\boldsymbol{\varepsilon}$ ($\varepsilon = \delta R_n y^{\varepsilon}$), where ε is an entry of $\boldsymbol{\varepsilon}$, R_n is a random number following the standard normal distribution, δ is the noise level, the accuracy of the re-constructed shapes will be considered.

Secondly, the uncertainty of the optimization algorithm can be quantified by the distribution of the solution, when the optimization is repeated n times with the random initial guess in the search space (Nguyen-Tuan et al., 2016), it is called sampling process. The samples of the optimizations are accessed by statistical methods accordingly.

2.6. Forward model: balance equations

The THM problems are formulated by a system of coupled balance equations. Equations for mass balance were established by following the compositional approach (Olivella et al., 1996). Constitutive equations are used to connect between the primary unknowns (i.e. displacements, liquid pressure, gas pressure and temperature) to the parameters and the dependent variables e.g. water saturation, energy flux and so on. In the sequel, we describe briefly the forward model by giving the most essential balance equations.

Mass balance of water: Water is present in the liquid phase. The total mass balance of water is expressed as follows:

$$\frac{\partial}{\partial t}(\theta_w) + \nabla \cdot (\boldsymbol{q}_w) = f^w. \tag{9}$$

where f^w is an external supply of water, θ_w is the volumetric mass of water, $\boldsymbol{q}_w$ is the advective fluxes.

Momentum balance for the medium: The momentum balance reduces to the equilibrium of stresses if the inertial terms are neglected as:

$$\nabla \cdot \boldsymbol{\sigma} + \boldsymbol{b} = \boldsymbol{0}, \tag{10}$$

where, $\boldsymbol{\sigma}$ is the stress tensor and $\boldsymbol{b}$ is the vector of body forces.

Internal energy balance for the medium: Heat transfer is modelled considering heat conduction of material and heat transport by means of mass motion. The equation for the internal energy balance for the porous medium is established taking into account the internal energy in each phase (E_s, E_l) as:

$$\begin{aligned}\frac{\partial}{\partial t}\left(E_s\rho_s(1-\phi) + E_w\rho_w\phi\right) + \\ \nabla \cdot (\boldsymbol{i}_c + \boldsymbol{j}_{Es} + \boldsymbol{j}_{Ew}) = f^Q,\end{aligned} \tag{11}$$

where, $\boldsymbol{i}_c$ is the energy flux due to the conduction through the porous medium, the fluxes $\boldsymbol{j}_{Es}$, $\boldsymbol{j}_{Ew}$ are advective fluxes of energy caused by mass motions and f^Q is an internal/external energy supply, ρ_s is the density of solid, ρ_w is the density of the liquid i.e. 1000 [kg.m^{-3}].

The final objective is to find the unknowns from the balance equations. Therefore, the dependent variables have to be related to the unknowns in the following constitutive relations. The constitutive relations of the coupled THM model includes thermo-elastic model for stress-strain relation, constitutive model for water transport (Darcy's law) and constitutive model for heat conduction (Fourier's law). The validation of the model in the non-damage case is reported in Nguyen-Tuan et al..

3. Application to Masonry Dams

3.1. Geometry and discretization

The cross section of the Fürwigge dam is used for forward and inverse simulations. The data are generated synthetically by solving the forward problem. To avoid inverse crimes (Colton and Kress, 2013), the generation of the synthetic measurements is performed on a different mesh from the inverse process. The geometry and discretization mesh, which can be seen in Figure 2, are used for synthesizing measurement data. This mesh has 2520 elements. In the inverse process, the geometry mesh has 3357 elements. It is assumed that the white elements is a damage zone where its material properties ($\boldsymbol{p}_m$) are defined by its porosity.

3.2. Damage indentification

The assumed damage zone is pure artificial and not related to the current working conditions of the Füwigge dam. The search space is illustrated in Figure 3. The noise level is $\delta = \pm 1$ and $\pm 5\%$. We chose a swarm size of 24 particles. The reason is that the convergence of the big swarm is faster than the convergence of the small swarm, and the big swarm will decrease the probability of the local minimum trap.

The measurement data, which are used to formulate the objective function, are established by the displacement, temperature, water pressure and the collection of the water outflow. Displacement are measured by 2 radar devices at the downstream side and pendulum for the upstream side, herein 11 measurement points are the selected (red rectangular points). Water pressures and temperatures are measured at the cyan circular points (10 points), the water pressures are additional measured at two more white points as it was designed in Fürwigge dam, see Figure 2. Thermocouples are used to measure temperature. Water pressures are measured by piezometers or tensiometers. The volume of water outflow at downstream side (magenta line) are measured at the collecting points (a, b, c, d and e). In numerical simulation, the water outflow is computed as in Eq. (8). The porosity is the unknown quantity and it varies in the bounds from 0.30 to 0.65.

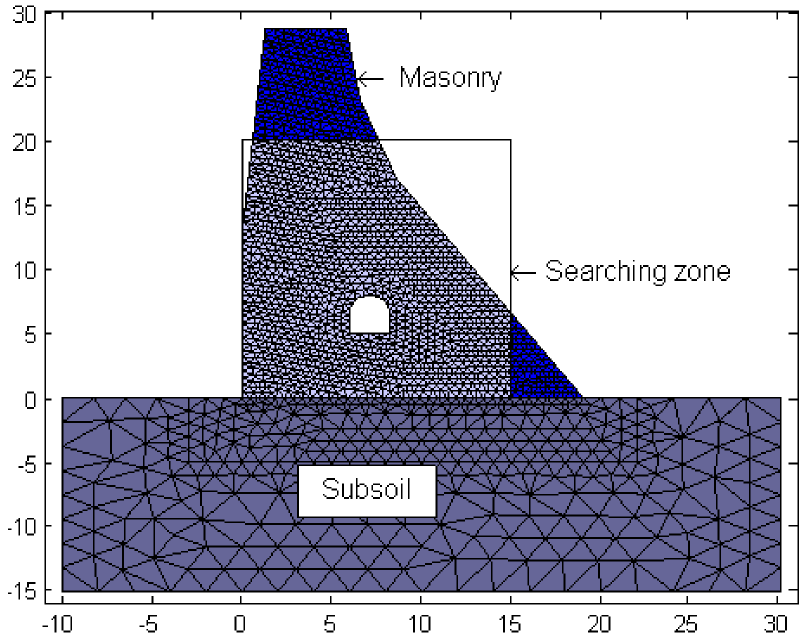

Figure 3. Materials and searching zone.

4. Results

Figure 4 presents the re-construction (inverse) solutions considering several noise levels. When the level of noise increases from ±1% to ±5% the uncertainty of the solutions increase, accordingly. The best objective functions presented in the figure is of the solution with ±1% noise level. The deterioration of the material properties is defined by the material porosity (ϕ). The solution in terms of porosity shows that the inverse solutions are close to the exact solution. The figure shows that the PSO method can be a good method for damage identification.

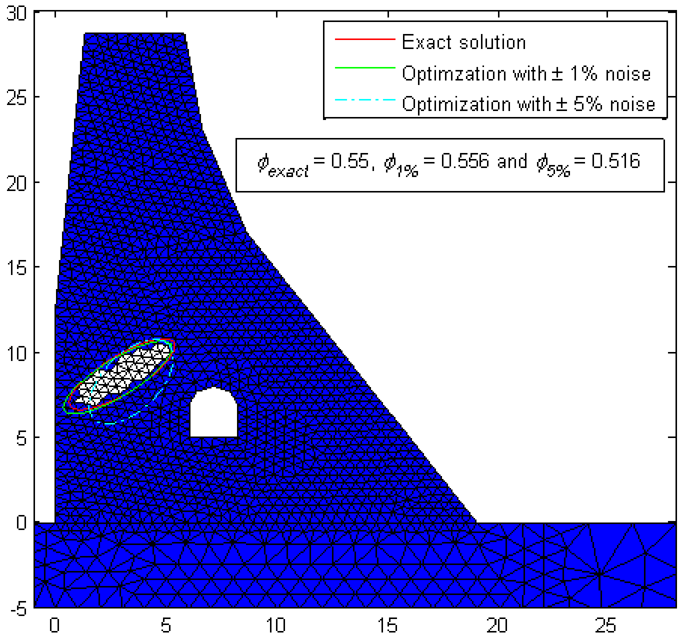

Figure 4. Results of optimization for different noise levels.

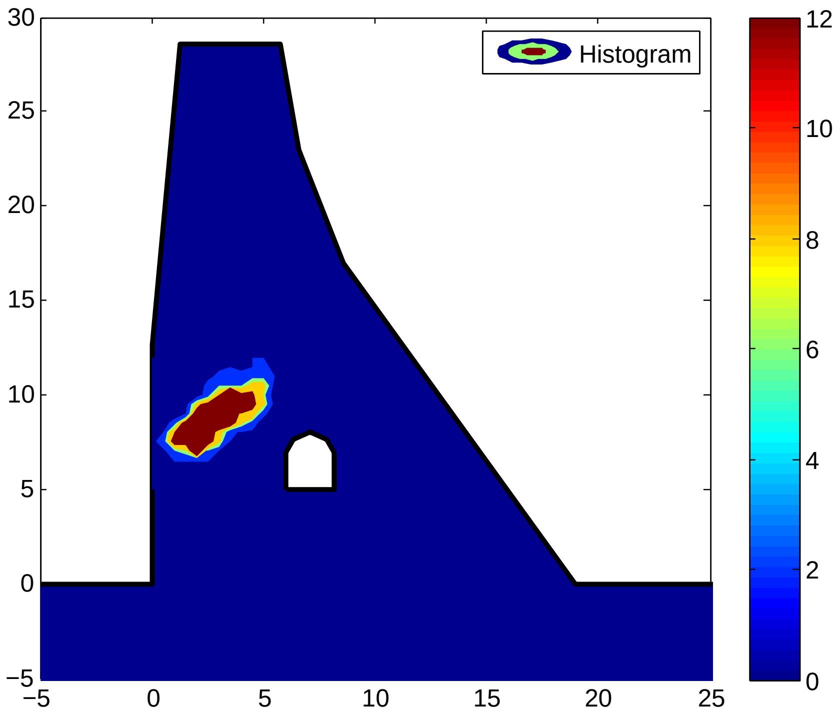

Figure 5. Histogram of the solutions ($\delta = 0\%$).

The inverse problem is solved repeatedly 15 times by PSO method. In order to avoid the dependence of the initial guess, the initial guesses of the particles are randomly uniform distributed in their search space. The histogram of the solution is presented in Figure 5. The color bar illustrates the frequency of the solutions which describe the damage zone. Certainly, the solution can not fit totally with the exact solution, because we used different meshes in the inverse and forward problems. It shows that the method can identify the damage zone with small uncertainty, when the noise level is zero. However, the uncertainty can also increase when the noise level increases. It can be recognized that the solutions are not identical with different initial guesses, however, the convergence of the solution is close to the exact solution.

5. Conclusion

In this paper, we introduce the method to not only detect the damage zone but also identify the severity of the damage. The severity of the damage is described by its material parameters in the coupled THM model. The PSO shows that it is a robust method in searching the minimum of the non-linear objective functions. The accuracy of the measurement data effects significantly the uncertainty of the results of the inverse problems. The uncertainty of the inverse problem can be quantified by the the probability distribution of the solutions obtained from the sampling process.

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