Effects of Measurement Error on the Genetic Algorithm in Soil Parameter Identification for an Earth- and Rockfill Dam

Effets des erreurs de mesure sur l'algorithme génétique lors de l'indentification des paramètres du sol pour un barrage en terre et enrochements

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ABSTRACT: It is usually difficult to determine values for soil parameter values in earth- and rockfill dams by traditional methods. Field sampling is not easily performed, especially in the impervious parts, since the performance and safety of the dam structure may be affected in an unfavourable way. Therefore other methods, preferably non-destructive, are needed to investigate the mechanical behaviour.

Inverse analysis has been utilised to identify soil parameter values for an earth- and rockfill dam. An error function and a genetic search algorithm were combined with a finite element software to perform the analysis. The model parameters in the chosen constitutive model were calibrated until the horizontal deformations corresponded to the horizontal inclinometer deformations.

Errors or irregularities in field measurements can occur, for instance based on the accuracy of the equipment. In this study, the performance of the genetic algorithm was investigated, when applied to identify soil parameters for a dam. Added perturbations to simulated inclinometer data are randomly generated within a chosen interval of error. The results showed that the genetic algorithm found a minimum for the error function even though the field data was substantially perturbed. Errors up to 10% were shown to have minor impact.

RÉSUMÉ: Sur les barrages en terre et enrochements, il est habituellement difficile de déterminer les paramètres mécaniques du sol à l'aide de méthodes traditionnelles. Les essais géotechniques *in situ* ne sont pas facilement réalisables étant donné qu'ils peuvent nuire aux performances et à la sécurité des barrages. Ceci est d'autant plus vrai sur les zones imperméables de ces ouvrages. Par conséquent d'autres méthodes, préférablement non destructives, sont nécessaires pour étudier le comportement mécanique de ces barrages.

Dans cette étude, l'analyse inverse a été utilisée pour identifier les paramètres constitutifs du sol d'un barrage en terre et enrochements. Une fonction d'erreur et un algorithme génétique ont d'abord été combinés à un logiciel aux éléments finis pour effectuer l'analyse inverse. Les paramètres du modèle constitutif choisi ont ensuite été ajustés afin que les déformations horizontales données par le modèle correspondent aux déformations inclinométriques.

Sur le terrain, l'occurrence d'erreurs de mesure est plausible et peut par exemple être due à la précision des équipements. Dans cette étude, la stabilité de l'algorithme génétique lors de la détermination des paramètres du sol du barrage en question a été examinée. Des perturbations ont été ajoutées aux donnés inclinométriques simulées au sein d'un intervalle d'erreur choisi. Les résultats ont montré que l'algorithme génétique était en mesure de trouver un minimum à la fonction d'erreur bien que les données de terrain étaient substantiellement perturbées. Les erreurs inférieures à 10% avaient un impact mineur sur la stabilité de l'algorithme.

KEYWORDS: dam, deformation, inverse analysis, genetic algorithm, soil parameter identification, perturbation

1 INTRODUCTION

In earth- and rockfill dams, information regarding the mechanical behaviour of the soil material in the dam zones is unfortunately often insufficient to provide a decent base for suitable constitutive modelling. Determination of soil parameters by traditional methods is not easily performed, especially in the impervious parts, since the performance and safety of the dam structure may be affected by sampling in an unfavourable way.

Inverse analysis, a non-destructive analytical method, can be utilised to obtain material parameters values for the constitutive models. A finite element (FE) model is calibrated until the behaviour observed in the simulation and monitoring correspond to each other. The calibration is performed automatically, by a search algorithm, until the discrepancy between modelled and real behaviour is minimised. Based on the inverse analysis theories by Tarantola (1987), the technique was introduced to the geotechnics by Gioda & Sakurai (1987). Since then, inverse analysis has been applied to various types of geotechnical applications by e.g. Swoboda et al (1999), Gens et al (1996), Calvello & Finno (2004), Levasseur et al (2008), Papon et al (2012) and de Santos (2015). Vahdati et al (2014) adopted inverse analysis to an earth- and rockfill dam. The genetic search algorithm was able to identify values for the material parameters that well captured the field behaviour, described by the horizontal deformations from an inclinometer. Identifying material parameters that are reliable forms a better base for modelling dam behaviour. Inverse analysis can thereby be a helpful tool in dam safety work.

The same dam as introduced by Vahdati et al (2014), Figure 1, has been studied. The objective here is to assess the effects of monitoring errors on the results produced by the search strategy. This is studied by perturbing the horizontal deformation values at the positions of an inclinometer. A synthetic case is considered, where the inclinometer data is simulated and thereby the optimum solution of input material parameter values is known in advance. The synthetic deformation values are perturbed within chosen intervals from 1% up to 100%. The effects on the search strategy are assessed in terms of proximity to the solution of the unperturbed synthetic case.

2 THE EARTH- AND ROCKFILL DAM

The analysed earth- and rockfill dam is 45 metres high, with a crest width of 6.5 metres. The inclination of the upstream slope is 1:1.85 (V:H) and 1:1.7 (V:H) for the downstream slope. The dam is built with a central impervious core of glacial till. Adjacent to the core, there are fine and coarse filters. As supporting zones, rockfill is placed on the sides of the coarse filter. The foundation in the analysed section consists of rock.

Table 1. Material parameter values for the constitutive model Hardening soil; dam body.

Zone	γ_{unsat} kN/m^3	γ_{sat} kN/m^3	$E_{50}^{ref} = E_{oed}^{ref} = \frac{1}{3} \cdot E_{ur}^{ref}$ MPa	m $-$	c kPa	ϕ' °	ψ °	$k_x = k_y$ *m/s*
Core	21	23	OPTIMIZED	0.8	20	38	0	3.0E-7
Fine filter	21	23	50	0.5	0	32	2	9.0E-5
Coarse filter	21	23	50	0.5	0	34	4	5.0E-4
Rockfill	19	21	OPTIMIZED	0.5	7	30	0	1.0E-2
Berms	21	23	10	0.5	7	30	0	5.0E-2

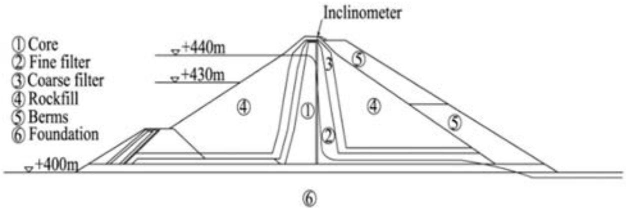

Figure 1. Cross section of the dam. After Vahdati et al (2014).

The studied dam is well equipped with various types of installations; measuring e.g. deformations, seepage etc. Deformation values from the position of a manual inclinometer, shown in Figure 1, are used in the analysis.

3 CONSTITUTIVE MODELS AND MATERIAL PARAMETERS

Vahdati et al (2014) found that the Hardening soil model was describing the soil behaviour of the dam reasonably well, therefore the model was chosen for this study too. For the foundation, the Mohr Coulomb model was chosen. Since the inverse analysis did not incorporate the foundation, a simpler constitutive model was considered as sufficient. More information on the models, as well as material parameter notations, can be found e.g. in Brinkgreve et al (2014) or Schanz et al (1999).

The values of the material parameters, corresponding to the chosen constitutive models, are shown in Table 1 and Table 2.

Table 2. Material parameter values for the constitutive model Mohr Coulomb; foundation.

γ_{unsat} kN/m^3	γ_{sat} kN/m^3	E MPa	v' $-$	c kPa	ϕ' °	$k_x = k_y$ *m/s*
19	21	10E3	0.2	0	42	1E-8

4 FINITE ELEMENT MODELLING

Since the studied dam is a long structure, it was appropriate to assume plane strain conditions and conduct two dimensional modelling. The utilised FE software was PLAXIS 2D 2011.

Minor modifications to the original cross section, shown in Figure 1, were performed when idealising the geometry into the FE programme, see Figure 2. The upstream toe berm was neglected due to the similarity in its material properties compared to the properties of the rockfill. Since consolidation time was not of interest, the horizontal filters were omitted.

The size of the geometry model was chosen so that the extent eliminated boundary effects. Standard fixities were chosen for generation of boundary conditions. The outer vertical boundary lines were normally fixed. The bottom boundary line was fully fixed.

Refinement of the mesh was performed especially in the area were the inclinometer is installed, to obtain higher accuracy of the computations and also because nodes need to coincide with the inclinometer measuring points. A suitable mesh for the computation accuracy was chosen by refinement until the results did not vary significantly. By this procedure a sufficient accuracy is obtained, for a minimum computation time.

All zones were modelled to represent drained behaviour, with exception of the core where undrained behaviour was assigned. This is represented by the option Undrained A using effective parameters in PLAXIS.

The dam body was built up in five steps, in this way a proper initial stress field is obtained. After construction of the dam and filling of the reservoir to +440 metres above sea level (m.a.s.l), the excess pore pressures were allowed to dissipate. Thereafter the reservoir level was lowered to +430 m.a.s.l, before the lower 20 metres of the downstream berm were built. This was followed by a raise to +440 m.a.s.l. and dissipation of excess pore pressures. In the next phase, the upper 20 metres were built. The deformations were reset to zero before the lower 20 metres were constructed. Deformations were measured directly after the final construction; excess pore pressures in the core were not dissipated.

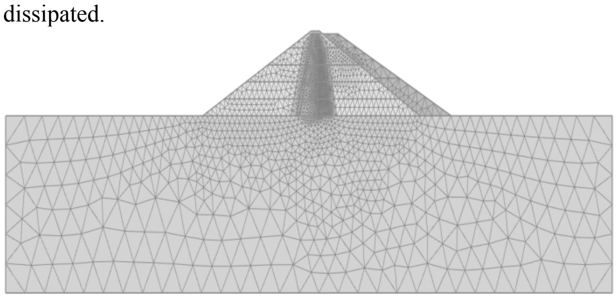
Figure 2. FE model of the dam. After Vahdati et al (2014).

5 SOIL PARAMETER IDENTIFICATION

5.1 *Error function*

The discrepancy between the measured values and the modelled values was evaluated by a scalar error function, suggested by Levasseur et al (2008). The error function was based upon the least-square method

$$F_{err} = \left(\frac{1}{N} \sum_{i=1}^{N} \frac{\left(U_{e_i} - U_{n_i}\right)^2}{\Delta U_i^{\,2}} \right)^{1/2} \quad (1)$$

where N is the number of measurement points, U_{e_i} the experimentally measured value, here deformations from an inclinometer. U_{n_i} is the corresponding deformation value from the numerical calculation. The error function has the unit of length. The parameter ΔU_i consists of two parts

$$\Delta U_i = \varepsilon + \alpha U_{e_i} \quad (2)$$

where ε represents an absolute error and the parameter α represents a dimensionless relative error. In this study, just as in Vahdati et al (2014), the focus is laid on the absolute error, meaning $\varepsilon = 1$ and $\alpha = 0$.

5.2 *Genetic algorithm*

The genetic algorithm (GA) is inspired by Darwin's theory of evolution. The GA, a form of artificial intelligence, was pioneered by Holland (1975). Goldberg (1989) later continued the development. The GA is a global optimization technique, which can provide a set of solutions close to the global optimum.

The process of optimization consists of some stages. Firstly, an initial population is created; which consists of a number of randomly generated individuals. The error function is evaluated for each individual. Thereafter the evolutionary processes selection, reproduction and mutation are applied. Only the individuals with the best fitness are chosen to be parents. In a random process the parents are paired to generate offspring. However, some offspring are randomly mutated. The next population will consist of the best parents and the best offspring. The processes are repeated until the average value of the error function for each new population does not vary significantly. Mutations are necessary for the solution not to converge too fast, before sweeping the search domain. Details concerning the GA can be found in Haupt & Haupt (2004).

5.3 *Optimization parameters, search domain and population size*

Sensitivity analyses, performed by Vahdati et al (2014), showed that the two most sensitive parameters for deformations at the inclinometer position are the reference secant stiffness, E_{50}^{ref}, of the core and of the rockfill. Therefore these two parameters have been chosen for the optimization.

The search domain was limited by lower and upper bounds for each search variable; based on the previous study by Vahdati et al (2014). The bounds for the search domain are: 5 MPa ≤ $E_{50,C}^{ref}$ ≤ 90 MPa and 5 MPa ≤ $E_{50,R}^{ref}$ ≤ 20 MPa; for the core and rockfill, respectively.

The initial population size of 240, with offspring generations of 120, was found to be suitable by Vahdati et al (2014) and is also applied to the present study.

6 PERTURBATIONS

All modelling was run towards a synthetic case, where the inclinometer data was simulated in the FE-programme. The optimum solution (OPT) is known as [$E_{50,C}^{ref}$, $E_{50,R}^{ref}$] = [56.250 MPa, 7.8125 MPa].

In order to investigate how the search strategy (GA) is affected by errors in the experimental data, the synthetic horizontal deformations from the inclinometer position are perturbed. Following a similar mathematical procedure as Mattsson et. al (2001), perturbations are randomly generated within a chosen interval

$$-x < \psi < +x \quad (4)$$

where $|x|$ represents the limits of the intervals and ψ is the randomly generated perturbation. Thereafter the horizontal deformation values are perturbed as

$$u_{x,\ perturbed} = u_x \cdot (1 + \psi) \quad (5)$$

where u_x is the deformation measured at each measurement point in the inclinometer. A new value for ψ is generated for each point of the inclinometer deformations. The global minimum is represented by the perturbation $\psi = 0$ when the solution corresponds to OPT. The following perturbation intervals, $|x|$, are considered: 1, 2, 4, 6, 8, 10, 20, 30 and 100%.

7 RESULTS

7.1 *Minimum solutions*

The obtained values for the optimization variables, $E_{50,C}^{ref}$ and $E_{50,R}^{ref}$, are plotted for the minimum value of the F_{err} for the intervals of perturbation. In Figure 3 the minimum solution for each interval is shown along with the global optimum (OPT), which represents the unperturbed case.

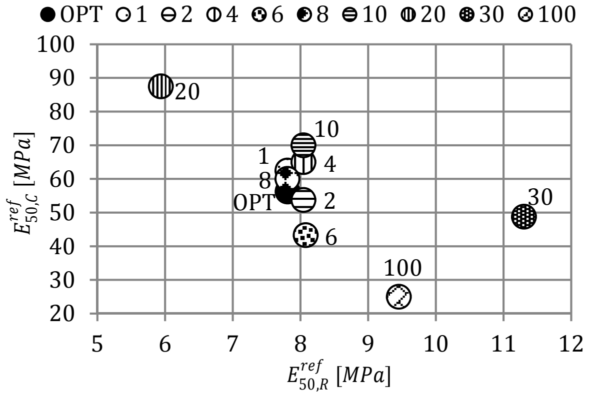

Figure 3. Minimum solutions for the perturbed deformation values.

For perturbation intervals up to 10%, the minimum solutions for each interval are gathering around the global optimum (OPT). For higher perturbation intervals, 20% and above, the distance from the global optimum to the minimum point increases.

The global minimum is not found exactly when searched for with perturbed deformation values. This should not be regarded as misbehaviour of the algorithm, but rather as a consequence of the introduction of the perturbed set of inclinometer values.

7.2 *Set of solutions*

The GA will produce many possible solutions; one method of indicating acceptable solutions is by choosing limits for the error function, F_{err}. A low value of F_{err} is chosen in order to visualise the behaviour of the sets of solutions, both for small and large perturbation intervals. In Figure 4 solutions for $F_{err} < 3 \cdot 10^{-3}$ are shown, for the perturbation interval 1%. The number of solutions is 560. However, only a limited amount of these are visible because points can represent multiple solutions and the solutions are gathered around the global optimum (OPT).

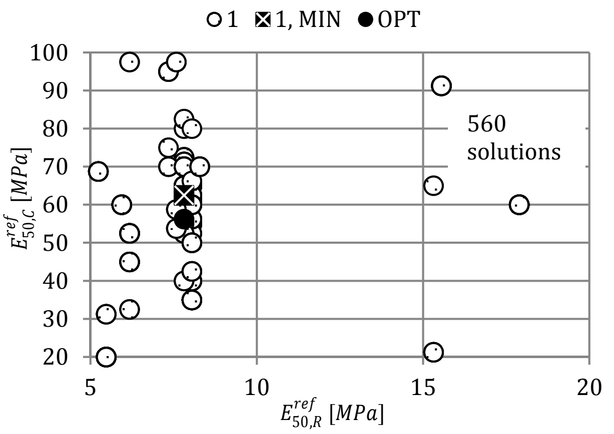

Figure 4. Solutions for perturbation interval 1%.

Sets of solutions are shown for the perturbation intervals 10% and 20%, see Figures 5 and 6. Similar spreading in the solutions is seen in Figure 5, compared to the solutions in Figure 4. From Figure 6, it can be seen that the spreading of the solutions increases compared to Figure 5. The number of solutions slightly decrease from the perturbation interval $|x| = 1$ and $|x| = 10$; a larger decrease is observed between $|x| = 10$ and $|x| = 20$.

The results in Figure 6 shows that solutions fulfilling $F_{err} < 3 \cdot 10^{-3}$ for $|x| = 20$, can be found near the optimum; even though the minimum point is further away from the optimum.

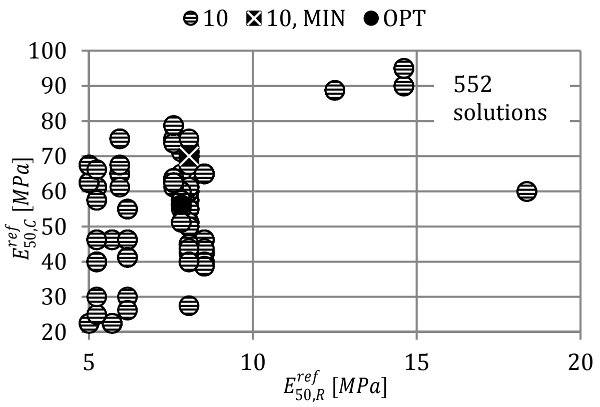

Figure 5. Solutions for perturbation interval 10%.

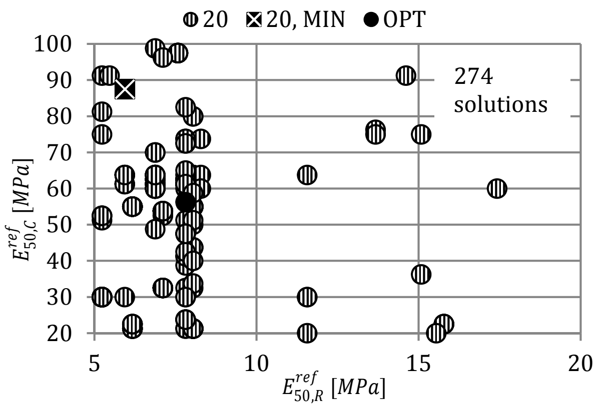

Figure 6. Solutions for perturbation interval 20%.

For $|x| = 30$ and $|x| = 100$ no solutions fulfilling $F_{err} < 3 \cdot 10^{-3}$ were found by the GA. With increased $|x|$, fewer solutions are found for $F_{err} < 3 \cdot 10^{-3}$. This trend implies that it is more difficult for the search strategy (GA) to deliver solutions with a low value of the F_{err} with increased $|x|$.

8 CONCLUDING REMARKS

This study gives an indication of how random measurement errors are affecting the performance of the search strategy. The genetic algorithm is able to find a minimum solution for the optimization parameters even though the field data is substantially perturbed. This shows that the search strategy can handle errors, which is beneficial when field data is considered where errors are likely to occur. However, if data containing errors is incorporated the found and the "real" solution can deviate from each other.

This study suggests that errors under 10% do not have large impact, on the results for this case. The genetic search algorithm can continue to find solutions near the global optimum. Larger errors than 10% present solutions that deviate significantly from the global optimum. However, the algorithm is continuing the optimization process and finding solutions without collapsing. This shows one of the strengths of the genetic algorithm.

In the utilised optimization code, the occurrence of errors can be taken into consideration by the error function. By giving the experimentally measured values more or less weighting; in this case by adjusting the values of ε and α.

9 ACKNOWLEDGEMENTS

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