Backanalysis of preloading

Analyse inverse de préchargement

Cristian de Santos
SAALG Geomechanics, Spain, cristian.desantos@saalg.com

Alberto Ledesma, Antonio Gens
Dept. of Civil & Environmental Engineering, Universitat Politècnica de Catalunya (UPC – BarcelonaTECH), Spain

ABSTRACT: The paper presents the application of a backanalysis methodology to the inverse analysis of preloading soft clays. The methodology is based on an appropriate selection of the objective function and it uses a novel adaptive genetic algorithm approach to solve the resulting optimization problem. The methodology is applied first to a synthetic example followed by an application to an intensely instrumented preload test. The selected observations are the evolution along time of displacements and pore water pressures. The key parameters to be identified are those with major influence on the results: compressibility and permeability of the soil. It is shown that the confidence in parameter estimation varies significantly depending on the time at which the observations are considered and the type of them (displacements vs. pore water pressure). The possibility of extrapolating early results to later stages of the preloading is also explored. The usefulness of the method in engineering problems is demonstrated by the application to a preloading performed to improve the soft ground of the Water Treatment Plant located in the Llobregat delta near Barcelona.

RÉSUMÉ : L'article présente l'application d'une méthodologie d'analyse inverse au cas de préchargements dans des couches d'argile molle. La méthodologie est basée sur la sélection appropriée de la fonction objectif et utilise une nouvelle approche basée sur un algorithme génétique adaptatif pour résoudre le problème d'optimisation qui en résulte. La méthodologie est premièrement appliquée à un cas d'étude synthétique puis au cas d'un essai de préchargement fortement instrumenté. Les mesures sélectionnées pour l'analyse inverse sont les registres temporels de déplacements des pressions d'eau interstitielle. Les paramètres clés à identifier sont ceux qui ont une influence majeure sur les résultats: compressibilité et perméabilité du sol. Il est montré que la confiance dans l'estimation des paramètres varie significativement en fonction du moment auquel les observations sont considérées et du type de celles-ci (déplacements ou pressions interstitielles). La possibilité d'extrapoler les résultats obtenus à des temps précoces aux étapes ultérieures du préchargement est également explorée. L'utilité de la méthode pour les problèmes d'ingénierie est finalement démontrée par l'application au cas du préchargement effectué pour améliorer le sol mou servant de fondation à l'usine de traitement des eaux située dans le delta du Llobregat près de Barcelone.

KEYWORDS: backanalysis, adaptive genetic algorithm and preloading

1 INTRODUCTION.

Preloading is a methodology that has been widely used to enhance soil properties, especially in cases where soft soils are involved. A critical aspect of that methodology is the consolidation time required to dissipate the pore water pressure, which is strongly linked with the geological profile and the compressibility and permeability of the materials composing it. Therefore, the proper definition of those parameters is vital to quantify the enhancement due to preloading. However, the task of determining those parameters is not usually straightforward.

In this paper, the backanalysis methodology presented in de Santos 2015 is used to identify the compressibility and the permeability of the soil, as well as the influence on the backanalysis of the time at which the observations are considered and the type of them.

2 BACKANALYSIS PROCEDURE.

On the field of geotechnics, backanalysis was firstly used at the end of the XX Century (Gioda & Sakurai 1987, Gens et al. 1996, Ledesma et al. 1996). A historical review of geotechnical backanalysis can be seen in Gens & Ledesma 2000.

As most techniques that identify parameters, backanalysis is based on minimizing a function that depends on the difference between measured variables and computed variables.

It is assumed that a fixed and deterministic model relates a set of variables, x, and a set of parameters, p. Some of the variables, x, are measured and form the vector of measurements, x^*. The best parameters are those that minimize the difference between measured variables and computed variables. A simple procedure to establish that, is defining the so called “objective function”, J:

$$J = \sum_{i=1}^{m} (x_i^* - x_i)^2 \tag{1}$$

where m is the number of measurements, i.e. soil displacements. J represents the error between the measurements and the same variables computed with the model. In this case, the objective function is based on the least squares criterion. Expression (1) can be generalized when measurements are not independent or have different errors, as it is shown in Ledesma et al. 1996. Note that J is a function of the parameters, as $x = M(p)$, where M represents the model. Minimising J will provide with the set of parameters that best simulate the measurements obtained.

It should be pointed out that J depends in a nonlinear manner on the parameters. The model M is usually represented by a Finite Element procedure, maybe with a nonlinear constitutive law. Even when a linear law is used, the objective function, J, is nonlinear with respect to the parameters p. That makes difficult to find the minimum of J.

2 .1 *Optimization technique: genetic algorithms*

There are many different optimization techniques to solve the problem of parameter identification, and among them, there isn't any technique that works better than the others for all different types of problems. However, genetic algorithms have proved themselves as a robust method for many different problems.

A genetic algorithm is an optimization method inspired by Darwin's theory of evolution and proposed by Holland 1975 and subsequently by Goldberg 1989. Genetic algorithm has been used in many different fields to optimize all kind of functions, but it was not applied in geomechanics until Levasseur et al. 2008. The algorithm is a stochastic global search technique, which does not need to compute derivatives and it works evaluating a cloud of possible solutions and selecting the best ones for the next iteration (generation). Crossover and mutation are the operators in charge of driving the search. Crossover is the one which exploits the areas with good potential solutions (individual) and mutation is the one which explores new areas where good potential solutions could be. The objective function is used to evaluate how good an individual is. This method does not guarantee that the optimum solution is found, but it can find relatively close solutions to the optimum, especially in problems with a large number of parameters.

In de Santos 2015, an exhaustive description of genetic algorithms and their application on the field of geotechnics is presented, as well as the introduction for the first time on the field of geotechnics of an adaptive genetic algorithm (AGA). An adaptive genetic algorithm is a type of genetic algorithm capable of adapting the probability of its operators, such as: selection, crossover, and mutation. The updated values of the probability of the operators are based on the diversity of the population, which is kept at a certain level to avoid premature convergence and increase the robustness of the algorithm.

3 SYNTHETIC CASE STUDY.

A synthetic case study has been used to analyze the influence on when to measure and what to measure to identify the compressibility and the permeability of a soft clay layer. To carry out this analysis, a numerical model defined by means of the geotechnical numerical software Plaxis 2D has been built. The model represents an 8-meter-thick soft clay layer under a load of 100kPa (see figure 1).

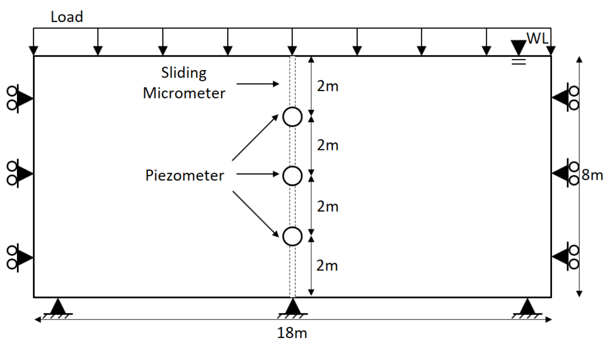

Figure 1. Synthetic case study geometry. WL: Water Level.

The Modified Cam-Clay constitutive model was used to simulate the soil behaviour. The parameters are shown in table 1.

Five different calculation phases were defined to simulate the application of a preloading and the subsequent process of pore water pressure dissipation:

- Phase 0: Initial stress generation.
- Phase 1: Preloading application (undrained conditions).
- Phase 2: 1 month of consolidation.
- Phase 3: 6 months of consolidation.
- Phase 4: 10 years of consolidation.

A total of 24 measurements of vertical displacements and 9 measurements of pore water pressure from three different times (at 1 month, 6 months and 10 years) were used in the analysis. The location of the measurements is shown in figure 1.

Table 1. Soil parameters. γ_{unsat}: unsaturated soil weight, γ_{sat}: saturated soil weight, K_x: horizontal permeability, K_y: vertical permeability, λ: isotropic compression index, κ: isotropic swelling index, ν: Poisson ratio, e_{init}: initial void ratio, M: tangent of the critical state line, φ: internal friction angle and ψ: angle of dilatancy.

Parameter	Value	Parameter	Value
γ_{unsat}	20 kN/m^2	κ	0.030
γ_{sat}	21 kN/m^2	ν	0.30
K_x and K_y (K_x=K_y)	$1\cdot10^{-9}$ m/s	e_{init}	0.80
λ	0.150	M	1
κ	0.030	φ	25º
ν	0.30	ψ	0º

As mentioned before, the main objective of this analysis is to study the influence on the backanalysis of what to measure (vertical displacements vs. pore water pressure) and when to measure (short term vs. long term). Therefore, the analysis was set out in terms of the objective function morphology study. The understanding of the morphology of the objective function can give us valuable information about the potential of the parameter identification itself, as well as the quality of it (de Santos, 2015). In this particular case study, due to the use of two different type of measurements, it was considered useful to define the objective function by means of the average relative error, expressed as J=A+B, where:

$$A = \frac{1}{N_{Uy}} \sum_{i=1}^{N_{Uy}} \left(\frac{U_{y\ i}^{me} - U_{y\ i}^{cal}}{U_{y\ i}^{me}} \right)^2 \tag{2}$$

$$B = \frac{1}{N_{Pw}} \sum_{j=1}^{N_{Pw}} \left(\frac{P_{w\ j}^{me} - P_{w\ j}^{cal}}{P_{w\ j}^{me}} \right)^2 \tag{3}$$

where N_{Uy} is the number of measurements of vertical displacements, $U_y{}^{me}{}_i$ is the *i-th* measurement of vertical displacements, $U_y{}^{cal}{}_i$ is the *i-th* calculated value of vertical displacement, N_{Pw} is the number of measurements of pore water pressure, $P_w{}^{me}{}_j$ is the *j-th* measurement of pore water pressure, and $P_w{}^{cal}{}_j$ is the *j-th* calculated value of pore water pressure.

In terms of soil parameters, the analysis has been focused on the permeability, K, and the isotropic compression index, λ, defining the modified Cam-Clay model.

In order to graphically represent the objective function, and subsequently study its morphology, a total of 1887 different combinations of permeability and λ were evaluated.

Some of the figures of the objective functions that have been generated depending on the type of measurement and the time when the measurements were obtained. Figure 2 illustrates the objective function only defined by vertical displacements one month after applying the preloading, while in figure 3, the definition of the objective function was only defined by pore water pressure one month after the preloading. Note that in figure 2 a well-defined minimum can be observed ($K=10^{-9}$m/s and λ=0.15). However, in figure 3, where pore water pressure was only used, the morphology of the objective function is represented by a flat valley along the vertical axis, indicating the complexity of identifying the compressibility, where different combinations of permeability and compressibility have similar value of objective function. Therefore, it seems that the pore water pressure, for this particular case study, does not provide enough information into the problem, especially as far as compressibility is concerned.

If vertical displacements and pore water pressure are combined, the resultant objective function is similar to the one obtained with only vertical displacements. Similar results were found when using the measurements 6 months after preloading.

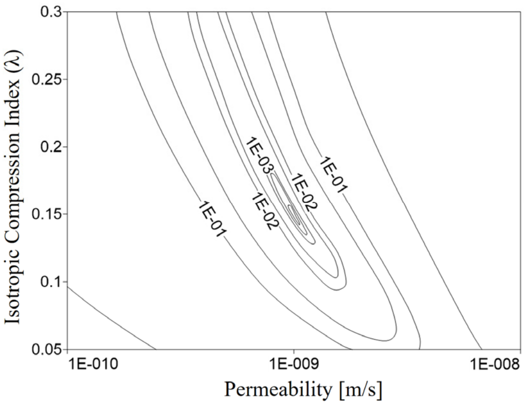

Figure 2. Objective function (J) defined only using vertical displacements (Uy) 1 month after applying the preloading.

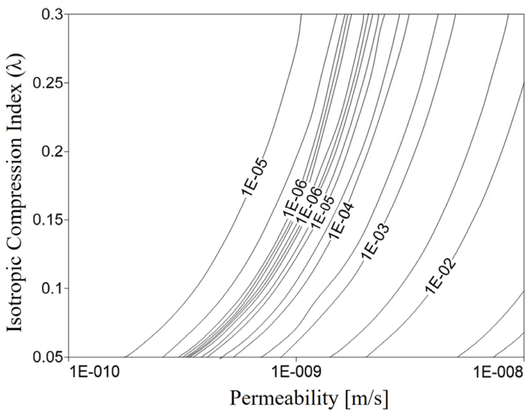

Figure 3. Objective function (*J*) defined only using pore water pressure (*Pw*) 1 month after applying the preloading.

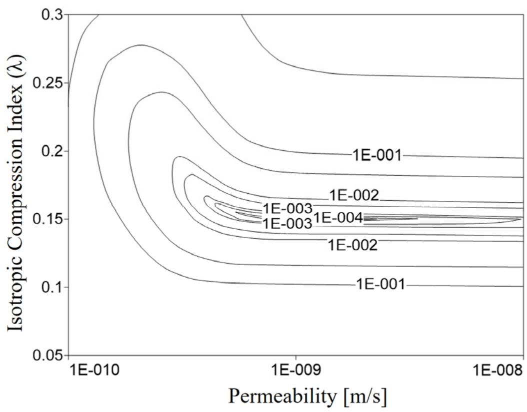

Figure 4. Objective function (*J*) defined only using vertical displacements (*Uy*) 10 years after applying the preloading.

On the other hand, when using the measurements for long term (10 years), different results were obtained (see figures 4 and 5). After 10 years of pore water dissipation, most of the excess pore water pressure due to the preloading has been dissipated, which caused that pore water pressure does not provide too much information into the problem. That is illustrated in figure 5 where large part of the space is flat.

Additionally, figure 4 suggests that permeability is difficult to identify when the excess pore water pressure is fully dissipated. In that scenario, the pore water pressure reaches the hydrostatic state and the displacements are independent to the permeability.

Finally, in figure 6, the morphology of the objective function defined with all measurements (vertical displacements and pore water pressure at 1 month, 6 months and 10 years) is shown. In this case, the minimum is well-defined by the morphology of the objective function, which coincides with the parameter values used to generate the measurements.

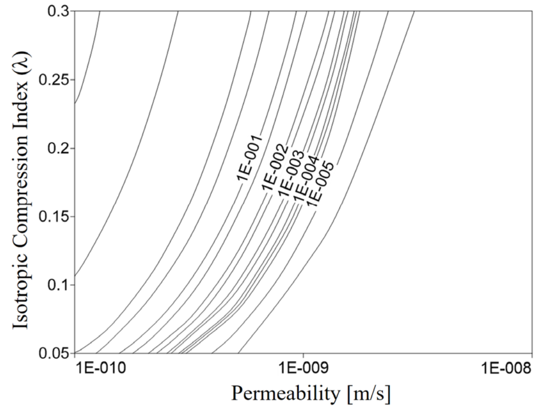

Figure 5. Objective function (*J*) defined only using pore water pressure (*Pw*) 10 years after applying the preloading.

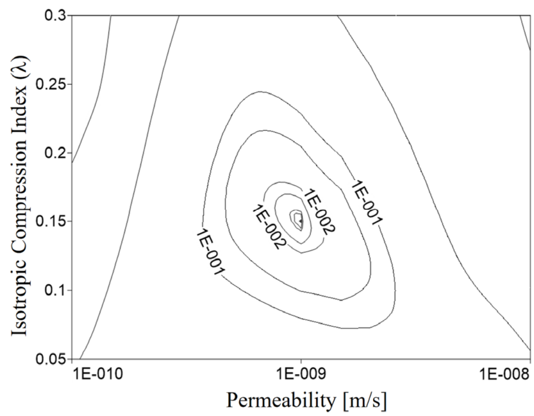

Figure 6. Objective function (*J*) defined using all measurements (*Uy* and *Pw* after 1 month, 6 months and 10 years of applying the preloading).

4 REAL CASE STUDY.

The real case study presented in this paper is a preloading test that was carried out to obtain information on precompression performance previous to the construction of a large water treatment plant. In Alonso et al. 2000, the procedure followed during the preloading test and an exhaustive analysis on the phenomenon of secondary consolidation associated with this case is described in detail.

The geological profile and the geometry of the problem are illustrated in figure 7, whereas the soil parameters are shown it table 2. Both clay layers (shallow and deep) contain significant numbers of sand and silty sand partings, which affect their hydraulic and mechanical properties. The gravels have not been represented as an actual soil layer in the model, its representation has been simulated as a drained boundary.

Figure 7. Geological profile and geometry of the real case study.

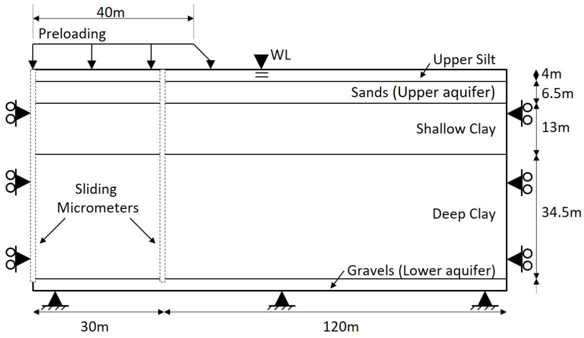

Table 2. Soil parameters. MC: Mohr-Coulomb, MCC: Modified Cam-Clay, UD: Undrained, D: Drained, E_{ref}: Young's modulus, c_{ref}: cohesion. The rest of the symbols are previously defined in table 1.

Parameter	Value	
	Upper Silt (MC - UD)	Sands (MC - D)
γ_{unsat}	20 kN/m^3	18 kN/m^3
γ_{sat}	21 kN/m^3	20 kN/m^3
K_x (K_x=K_y)	$1 \cdot 10^{-9}$ m/s	-
E_{ref}	10000 kPa	100000 kPa
c_{ref}	10 kPa	0 kPa
ν	0.30	0.3
φ	28	35
ψ	0	0
	Shallow Clay (MCC - UD)	Deep Clay (MCC - UD)
γ_{unsat}	20 kN/m^3	20 kN/m^3
γ_{sat}	21 kN/m^3	21 kN/m^3
K_x (K_x=5K_y)	$1 \cdot 10^{-3}$ -$1 \cdot 10^{-9}$ m/s	$1 \cdot 10^{-8}$ - $1 \cdot 10^{-10}$ m/s
λ	0.02 - 0.15	λ = 5κ
κ	κ = λ/5	0.004 - 0.031
ν	0.3	0.3
e_{init}	0.8	0.8
M	1	1
φ	25	25
ψ	0	0

The numerical software Plaxis 2D was used to build the model. Six different calculation phases were defined in order to reproduce the preloading test and the previous stress state history:

- Phase 0: Initial stress generation.
- Phase 1: Water pumping of the lower aquifer (lowering 25m of water).
- Phase 2: Partial pore water pressure recovery of the lower aquifer (increasing 20m of water).
- Phase 3: Preloading application (80kPa in 53 days).
- Phase 4: 61 days of consolidation.
- Phase 5: 208 days of consolidation.

To carry out the backanalysis, a total of 228 measurements of vertical displacement were used. The measurements were extracted from two sliding micrometers (see figure 7). Two sets of measurements were introduced in the analysis, one equivalent to the calculation phase 3, and the other equivalent to phase 4. However, in figure 8, where the measurements from the sliding micrometer located in the centre of the preloading are compared with the results from the backanalysis, the measurements of phase 5 are also shown to illustrate the model capacity of prediction.

The parameters identified in this backanalysis are: the permeability and the isotropic compression index, λ, of the shallow clay, and the permeability and the isotropic swelling index, κ, of the deep clay.

In this particular case study, an adaptive genetic algorithm was used to optimize the objective function.

The results of the backalanysis are shown in table 3, which are associated with the best individual after 10 generations and 325 evaluations over 334125 possible solutions.

Table 3. Backanalysis results.

Shallow Clay	Deep Clay
$K_x = 5 \cdot 10^{-8}$ m/s (K_x=5K_y)	$K_x = 5 \cdot 10^{-9}$ m/s (K_x=5K_y)
λ = 0.035 (λ=5κ)	κ=0.0175 (κ=λ/5)

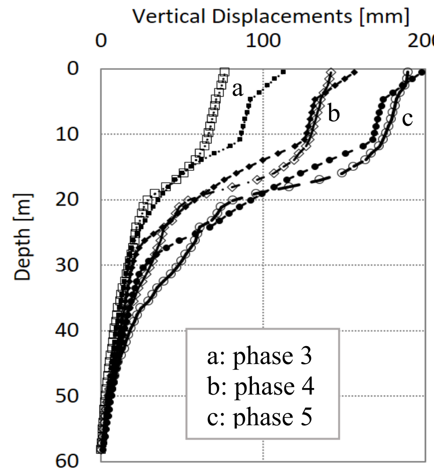

Figure 8. Measurements vs. calculations. The empty symbols are measurements and the filled symbols (black) are the calculations.

5 CONCLUSION

This paper presents the application of backanalysis on preloading problems, using finite element method and genetic algorithms. The systematic application of backanalysis can become a very valuable tool of control, which helps to predict with less uncertainty the evolution of preloading. A synthetic case study is presented to illustrate different objective function morphologies that can be obtained. The application of the methodology in a real case study to identify the permeability and the stiffness of a soft clay using field measurements is presented as well.

6 REFERENCES

Alonso, E.E., Gens, A. & Lloret, A. (2000). Precompression design for secondary settlement reduction. Géotechnique, 50(6):645-656.

de Santos, C. (2015). Backanalysis Methodology Based on Multiple Optimization Techniques for Geotechnical problems. PhD Thesis. Technical University of Catalonia - UPC - BarcelonaTECH, Barcelona, Spain.

Gens, A., Ledesma, A., Alonso, E.E. (1996). Estimation of parameters in geotechnical backanalysis – II Application to a túnel excavation problem. Computers and Geotechnics, 18, 29-46.

Gens, A., Ledesma, A. (2000). Análisis inverso e identificación de parámetros en Geotecnia. Libro Homenaje a J.A. Jiménez Salas, "Geotecnia en el año 2000". CEDEX, Ministerio de Fomento, Madrid.

Gioda, G., Sakurai, S. (1987). Back analysis procedures for the interpretation of field measurements in geomechanics. Int. J. Num. Anal. Meth. Geomechanics, 11, 555-583

Goldberg, D.E. (1989). Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley, MA, USA.

Holland, J.H. (1975). Adaptive in Nature and Artificial Systems. University of Michigan Press. Ann Arbor, MI, USA.

Ledesma, A., Gens, A., Alonso, E.E. (1996). Estimation of parameters in Geotechnical backanalysis – I. Maximum likelihood approach. Computers and Geotechnics, 18, 1-27.

Levasseur, S., Malécot, Y., Boulon, M. & Flavigny, E. (2008). Soil parameter identification using a genetic algorithm. Int. J. for Num. Analyt. Methods in Geomechanics, 32(2):189-213.