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OPTIMAL SENSOR LOCATION FOR PARAMETER IDENTIFICATION IN SOFT CLAY

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Abstract. *Performing parameter identification prior to numerical simulation is an essential task in geotechnical engineering. However, it has to be kept in mind that the accuracy of the obtained parameter is closely related to the chosen experimental setup, such as the number of sensors as well as their location. A well considered position of sensors can increase the quality of the measurement and to reduce the number of monitoring points. This Paper illustrates this concept by means of a loading device that is used to identify the stiffness and permeability of soft clays. With an initial setup of the measurement devices the pore water pressure and the vertical displacements are recorded and used to identify the afore mentioned parameters. Starting from these identified parameters, the optimal measurement setup is investigated with a method based on global sensitivity analysis. This method shows an optimal sensor location assuming three sensors for each measured quantity, and the results are discussed.*

1 INTRODUCTION

Identifying the correct soil parameters is essential to perform a reasonable numerical simulation of a geotechnical problem. As the behaviour of soft clay is very complex, laboratory experiments are required to determinate its parameters. Therefore, for these experiments a correct planning is necessary and can be decisive for the quality of the gained results. The methodology of optimal experimental design (OED) is not established in the field of geotechnical engineering and few examples are known from civil engineering [1]. Other scientific fields use this technique to improve the significance of their experiments (for instance see [2] and [3]) During this study, the question is: "Where should the vertical displacement and the pore water pressure be measured in an experimental device to identify the soil's parameters most precisely? " Translated to the way of thinking of the OED, the variable parameters are the spacial coordinates of the sensor location and the corresponding parameter space is the boundaries of the loading apparatus. To detect these sensor locations, this study's approach is to use the global sensitivity analysis (GSA). This method indicates by which parameter a certain output is influenced and is well proven in geotechnical engineering (see [4] and [5]). In this method, to precisely identify parameters, it is necessary that the output of interest has a high sensitivity towards the used parameter. Consequently, when comparing the sensitivity of the same parameter in different points, the point that indicates the highest sensitivity should be most suitable for the parameter identification.

2 EXPERIMENTAL PROGRAM

The numerical model that is presented in the next chapter simulates a cross section of the experimental devise corresponding to the left part of figure 1. This device and its operating mode have been presented first in [6]. The right wall of the box in this cross section is impermeable as well as the left one and the membrane between water and soil area at the top that separates the soil from the water. During the whole process displacement of soil medium is recorded in the cross-marked spots, while the pore water pressure (u_w) is recorded by three pressure transducers below the loading plate. The dark grey area represents the examined reconstituted Kasaoka clay that is initially consolidated by means of the uniformly distributed air and water pressure on top. The main experiment is started by applying 30 kPa by the loading plate on one side of the soil specimen. Afterwards a consolidation time of one hour takes place. Then the process of increasing load and consolidation is repeated two more times, leading to a total loading of 90 kPa. The experiment is concluded by a 100 hours consolidation, leading to a total dissipation of the developed u_w. The dissipation excess pore water pressure occurs via the permeable boundary at the bottom.

3 NUMERICAL FORWARD MODEL

Soft soils and especially clay have an explicit time depending hydro-mechanical behaviour. That means structures built on clayey soils do not only exhibit large settlements right after loading process, but some settlements can take place over a very large time period, known as consolidation. In the present work the modified cam clay model [12] is selected to simulate the current case. It has six constant parameters, as follows: the compression index λ ($\equiv$ loading

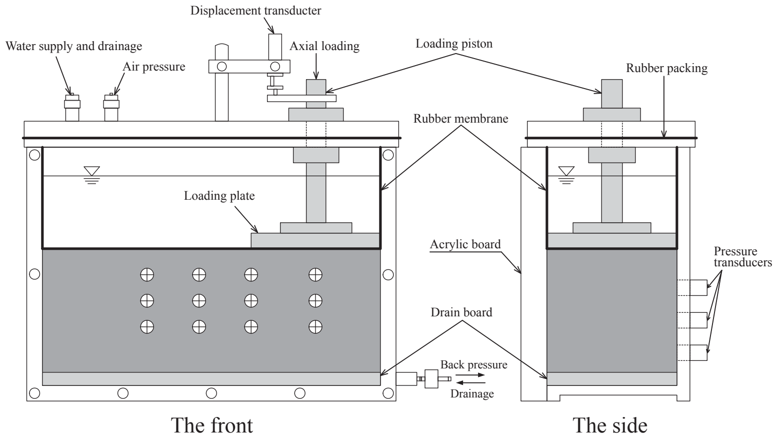

Figure 1: Experimental device [6]

stiffness), the swelling index κ ($\equiv$ unloading stiffness), the slope of critical state line M, the Poisson ratio ν, the permeability $k_x = k_y$ (initially constant in both directions), and the change ratio of permeability due to reduction of void ratio c_k.
The experimental process was simulated in a 2D-model created with the FEM-based code Plaxis 2D. The boundaries on the sides are assumed to be fixed and impermeable, while the bottom allows no deformations but is permeable. The top boundary is impermeable to consider the rubber membrane. The distributed loads that are applied to model the water pressure and the loading plate can cause displacements.

4 PARAMETER IDENTIFICATION

To capture any possible combination, the ranges for the parameter identification were explicitly chosen very large, corresponding to [7] and [8]. Out of these ranges, 100 parameter samples using latin hypercube sampling were created. The numerical model was run for each parameter sample and the u_w and U_y values were recorded at the end of the loading and consolidation phases. As performing parameter identification within an optimisation analysis process needs to run hundreds times the model a huge amount of time or computational effort is needed. Therefore, a metamodel is trained out of the input and output data, based on a mathematical function, namely the least square method to substitute the numerical model. In this way the optimisation algorithm can be applied to any parameter combination in a very short time, without need of running the time consuming FE-code.
To find the optimal parameter set the least square method is defined as objective function, reducing the distance between the simulated and measured values of U_y and u_w in the three points below the loading plate (figure 1). The process of optimisation itself is performed using the generic algorithm within the “Matlab Optimization tool ” [9].
After being identified these parameters are applied in the numerical forward model and the resulting curves for the u_w and U_y are plotted in figure 2. Regarding the curves describing the u_w-distribution, a high agreement can be seen between the measurements and their corresponding simulation data, especially after the last loading. The displacement curves in the right part of figure 2 show qualitatively good result and the final values at the end of the final consolidation are almost matched. During the loading phases the settlement grow to fast indeed. The aspect

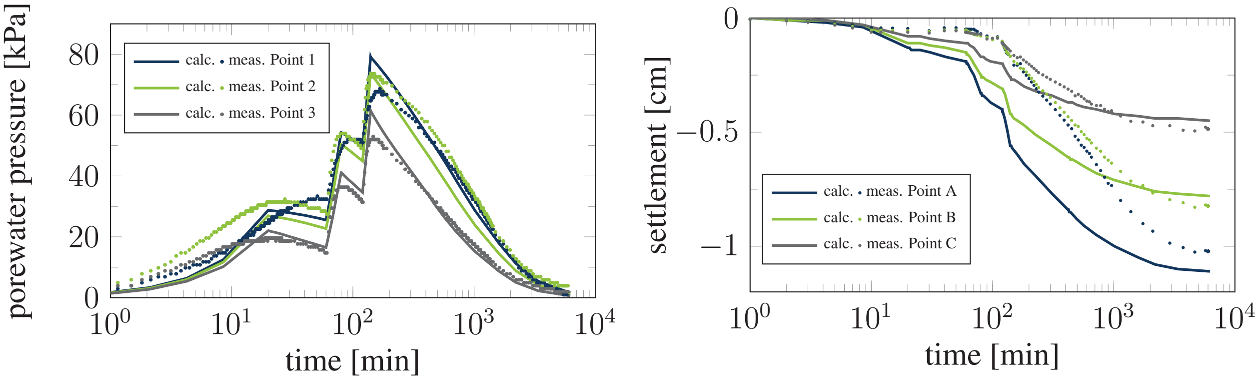

Figure 2: Optimised simulation data for u_w and U_y versus time

that has to be considered is that maybe the measurements from the three points that were used to identify the parameter do not contain enough information to perform a reliable identification. This is the initial thought that motivates the current work.

5 IDENTIFICATION OF OPTIMAL SENSOR LOCATIONS

5.1 Determination of sensitivity distribution

The basic definition of sensitivity analysis is the study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input [10]. Global sensitivity analysisis run in this study by variance based method. The main idea of variance based methods VB is to evaluate how the variance of inputs contribute into the variance of the model output. The total effect sensitivity index S_{Ti} is a more comprehensive index which indicates the influence of input factors and their coupling terms with the other input factors. The procedure for calculation of first order and total effect sensitivity indexes has been presented by Saltelli [10].

The results of the GSA in a point below the loading are shown in figure 3. As the most important parameters are the permeability k and the loading stiffness λ, the ongoing work focusses on these parameters. For the GSA, it is necessary to have a variation of the input parameters and therefore changing results. However, as the soil parameters are already identified, the parameter ranges can be reduced and the correlation between stiffness and permeability is considered to have a more accurate soil behaviour description. For the following GSA 100 samples of permeability are created within the reduced range of $[1.3E-9$ - $1.3E-8]$. The corresponding stiffness values are generated, according to [12] and [11], resulting in a range for λ of $[0.251$ - $0.361]$. All of these parameter samples are run in the numerical forward model to create a metamodel as described in section 4. The difference is that this time the results are not only recorded in one point, but for 152 locations, distributed over the whole system, but concentrated below the loading area. Subsequently, GSA is performed in each of this points for U_y and u_w with respect to the permeability k and the stiffness λ to gain the sensitivity indices S_{Ti}.

As the parameter identification is based on real measurement values which include an uncertainty, the results are falsified. Assuming that the uncertainty is a first order error, the larger the measured values are, the higher the reliability of these values are. Therefore it is reasonable to consider not only the sensitivity but also the variance of a certain output by multiplying them with each other.

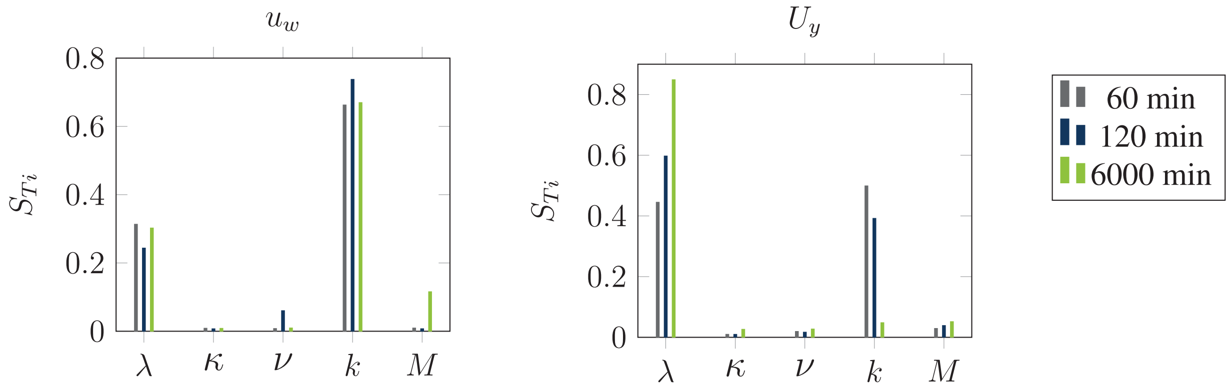

Figure 3: GSA-indices S_{Ti} for point P1

6 RESULTS

The output of the 100 FE- simulations which were used to create the metamodel are also used to compute the variance of both output values of outputs in each of the mentioned 152 points. Finally, the variance of each point is multiplied with the corresponding sensitivity index $S_{Ti}(x, y)$. The results are displayed as contour plots presenting the product, distributed over the whole space of the experimental surface (see figure 4). In case (a) a large area of high sensitivity can be seen below the loading area with even increasing sensitivity in lower areas. Below the loading plate u_w has its highest values, but is strongly related to the applied load on top and less to the permeability k. The only possibility for u_w to dissipate is through the boundary at the bottom of the experimental device. The explanation for the shape of figure 4(b) is closely related to figure 4(a). The time point that is considered is at the end of a simultaneous loading and consolidation phase, which means below the loading plate u_w is high and the presence of excess pressure prevents soil-stiffness induced settlements. In the bottom area u_w can dissipate and soil deformation is again related to the stiffness λ.

At the position $(x = 0.15, y = 0.095)$ the settlements are quite small, as this describes the limit of the loading area. However in this point not only compression takes place, but here there are also shear stress. This shear stress influences the void ratio and according to [11] and [12] the change in void ratio also changes the soil's stiffness and its permeability. This explains the shape of the plots figure 4(c) and (d), as there the most sensitive behaviour is observed in the same mentioned area.

According to the gained results one could suggest measurement devices for the vertical displacements at the positions $(0.15, 0.095)$, $(0.18, 0.03)$, and $(0.21, 0.095)$. The measurement of u_w could be useful at $(0.15, 0.095)$, $(0.18, 0.01)$, and $(0.21, 0.01)$. One should consider that technical feasibility can be limiting when rearranging the sensors, especially in areas near the boundaries. Having such information could help to reduce uncertainties and computational work as the employed data is reduced.

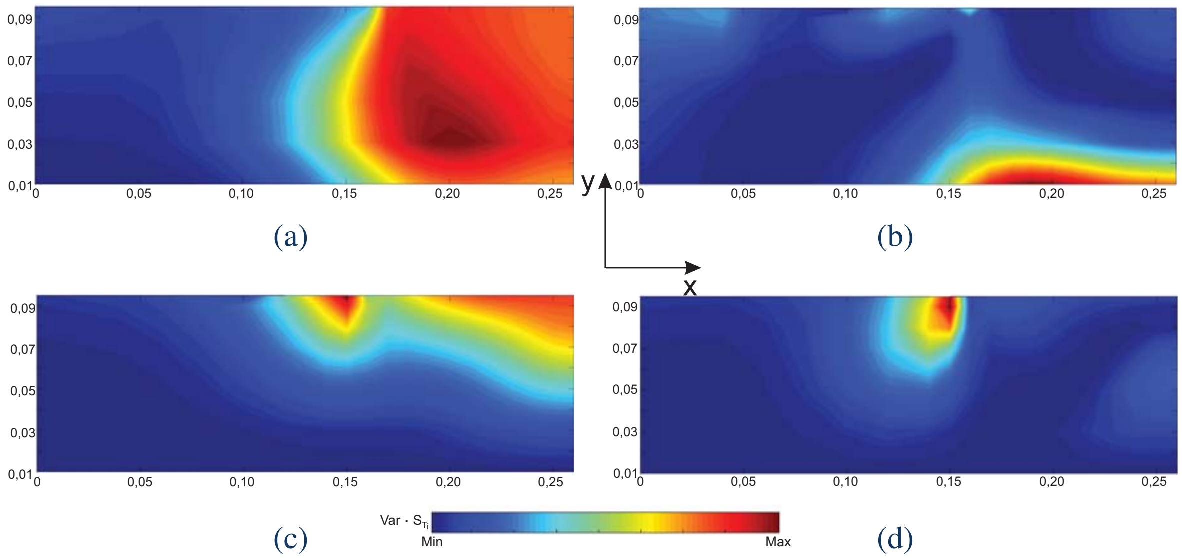

Figure 4: Sensitivity distribution for u_w towards k (a) and λ (b), and for U_y towards k(c) and λ (d)

REFERENCES

[1] T. Lahmer: Optimal experimental design for nonlinear ill-posed problems applied to gravity dams. Journal of Inverse Problems, **27 (12)**, 2011.

[2] R. Schenkendorf: Optimal Experimental Design for Parameter Identification and Model Selection. Phd-Thesis, Otto-von-Guericke-Universität Magdeburg, 2014.

[3] D. Uciński: Optimal Measurement Methods for Distributed Parameter System Identification. CRC Press, Boca Raton, 2005.

[4] S.Miro, D. Hartmann and T. Schanz: Global sensitivity analysis for subsoil parameter estimation in mechanized tunneling. Computers and Geotechnics, **56**, 80–88, 2014

[5] K. Khaledi, E. Mahmoudi, M. Datcheva, D. König, T. Schanz: Sensitivity analysis and parameter identification of a time dependent constitutive model for rock salt. J. of Comp. and App. Mathematics, In Press, Accepted Manuscript.

[6] S. Nishimura, T. Shuku and K. Fujisama: Prediction of Multidimensional Deformation Behavior Based on Observed Values. Int. J. Geomech., **40 (3)**, 401–411, 2014.

[7] J.E. Bowles: Foundation Analysis and Design. McGraw-Hill, London, 2001.

[8] B.M. Das: Principles of Geotechnical Engineeringm. Thomson, Toronto, 2006.

[9] J.H. Holland: Adaptive in Natural and Artificial Systems. University of Michigan Press, Ann Arbor, 1975.

[10] A. Saltelli et al.: Global Sensitivity Analysis: The Primer. John Wiley, New York, 2008.

[11] D. W. Taylor: Fundamentals of Soil Mechanics. John Wiley, New York, 1948.

[12] A. N. Schofield and C. P. Wroth: Critical state soil mechanics, McGraw-Hill, London, 1968.