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DOI
10.1201/9781003431749-145

Publication date
2024

Document Version
Final published version

Published in
Proceedings of the XVIII ECSMGE 2024

Proceedings of the XVIII ECSMGE 2024
GEOTECHNICAL ENGINEERING CHALLENGES
TO MEET CURRENT AND EMERGING NEEDS OF SOCIETY

ISBN 978-1-032-54816-6
DOI 10.1201/9781003431749-145

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Détermination, optimisation et sélection des paramètres d'un modèle constitutif avancé à l'aide d'une base de données d'essais triaxiaux et d'outils d'apprentissage automatique

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ABSTRACT: Numerical modelling in Geo-Engineering is used to solve complex problems by simulating, analysing, or predicting soil behaviour under certain loading and boundary conditions. The soil behaviour is simulated by constitutive models that describe the relationship between stresses and strains through a mathematical formulation. Model parameters are used to calibrate model behaviour to physical soil behaviour measured during in-situ testing (e.g. CPT) or laboratory testing (e.g. triaxial testing). The selection of model parameters is challenging as it needs to cope with aspects as, constitutive model limitations, laboratory test limitations, sample disturbance, soil heterogeneity and many other. In this paper a database with over 3000 stress-strain paths measured during triaxial tests is used to derive model parameters for the Hardening Soil Small Strain Stiffness model (HS small). A procedure/algorithm has been developed to calibrate model parameters by comparing measured stress-strain paths to a simulated response from a single stress point constitutive driver. Several data analysis techniques, including machine learning tools, have been used to investigate the relationship between soil properties, soil parameters and HS small model parameters. In this paper the developed methodology and the results of the data analysis are presented.

RÉSUMÉ: La modélisation numérique en géo-ingénierie est utilisée pour résoudre des problèmes complexes en simulant, analysant ou prédisant le comportement du sol sous certaines charges et conditions limites. Le comportement du sol est simulé par des modèles constitutifs qui décrivent la relation entre les contraintes et les déformations par le biais d'une formulation mathématique. Les paramètres du modèle sont utilisés pour calibrer le comportement du modèle par rapport au comportement physique du sol mesuré lors d'essais in situ (par exemple CPT) ou d'essais en laboratoire (par exemple essais triaxiaux). La sélection des paramètres du modèle est un défi car elle doit prendre en compte des aspects tels que les limites du modèle constitutif, les limites des essais en laboratoire, la perturbation de l'échantillon, l'hétérogénéité du sol et bien d'autres. Dans cet article, une base de données contenant plus de 3000 trajectoires de contrainte-déformation mesurées lors d'essais triaxiaux est utilisée pour dériver les paramètres du modèle de rigidité des sols durcissants à faible déformation (HS small). Une procédure/algorithme a été développée pour calibrer les paramètres du modèle en comparant les trajectoires de contrainte-déformation mesurées à une réponse simulée à partir d'un pilote constitutif à point de contrainte unique. Plusieurs techniques d'analyse de données, y compris des outils d'apprentissage automatique, ont été utilisées pour étudier la relation entre les propriétés du sol, les paramètres du sol et les paramètres du modèle HS small. Cet article présente la méthodologie développée et les résultats de l'analyse des données.

Keywords: Triaxial test; parameter determination; constitutive models; machine learning.

1 INTRODUCTION

Numerical methods, like the finite element method (FEM), have gained popularity and an increasing importance in Geo-engineering. They are widely accepted and are now considered a standard design tool. This is firstly because the (commercial) software has been developed to the point where it is easy to operate and secondly because of the availability of appropriate constitutive models that describe the mechanical behaviour of soils in a continuum framework (Schweiger et al. 2019). Model parameters are required to quantify certain features of the soil behaviour. In general, simple constitutive models require less input parameters than more advanced models, but they may therefore lack some essential features of soil behaviour (Brinkgreve et al. 2010). Parameter determination is a heavily debated and researched topic in the field of Geo-Engineering, due to the complexity of these heterogeneous, natural building materials and the amount of engineering judgement required. This paper aims to elaborate on the methodology (Chapter 2), results and discussion (Chapter 3), and conclusion (Chapter 4) of the parameter determination, optimisation and selection for the HS small model parameters.

2 METHODOLOGY

Over the past decades a large number of triaxial tests on soil samples from across the Netherlands have been conducted by Fugro Netherlands according to the NEN-EN-ISO 2018 standard, or one of its predecessors. This data offers the opportunity to perform an analysis on, and research (new) statistics and correlations based on the full measured stress paths. This paper focuses on the Consolidated Isotropic Drained and Undrained Multi Stage triaxial tests.

2.1 Soil properties

Each text file, in which the triaxial test measurements are stored contains information regarding the soil sample like the initial weight, dry weight, volumes etc. With this information soil properties can be determined $(\gamma, w, \gamma_d, e_0 \; and \; n)$, which provide information about the soil sample. These results can be used to formulate correlations with other parameters.

2.2 Soil parameters

The triaxial measurements were used to derive the classic soil parameters, the internal friction angle (φ') and the cohesion (c') were determined at 2% strain using the p-q stress space, also known as the Cambridge stress space (Roscoe et al. 1958). The stress-strain path was used to determine the secant stiffness (E_{50}) at 50% peak deviatoric stress. Determining the stiffness as such for different confining stress levels also enables determining the power of stress level dependency of stiffness (m).

2.3 Model parameters

The Hardening Soil with small-strain stiffness (HS small) was selected as constitutive model to describe the stress-strain relationship of all tested soils, since it is an advanced model for soil in general (Brinkgreve 2005). It requires 13 model parameters. An initial parameter set was derived by expanding upon the soil parameters, using common correlations and default values from the literature (the traditional method). A simulation of the triaxial test is performed using the SoilTest facility in the PLAXIS software package using this initial parameter set and the stress-strain path is compared to the laboratory measurement (Figure 1). It can be seen that the simulation with the initial parameter set is not optimal in approximating the measurement, since this is only the starting point of the optimisation algorithm.

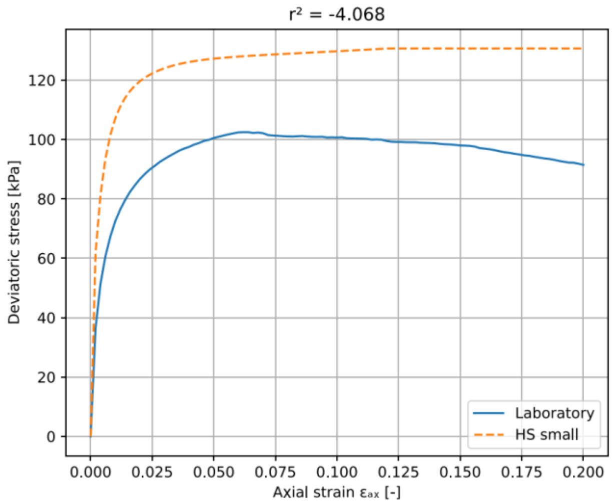

Figure 1. Example of comparison of triaxial test simulation with the initial parameter set (HS small with measurement (Laboratory)).

The procedure is to fit the stress-strain path of the simulation to the measured stress-strain path in the laboratory by calibrating the HS small parameters. The goodness of the fit will be quantified using the coefficient of determination (r^2) and the aim is to reach a value close to 1, where $r^2 = 1$ is a perfect fit. The schematic overview of the algorithm is presented in Figure 2. The sequence in which the parameters were optimised was based on the sensitivity of the individual parameter with regard to the test results.

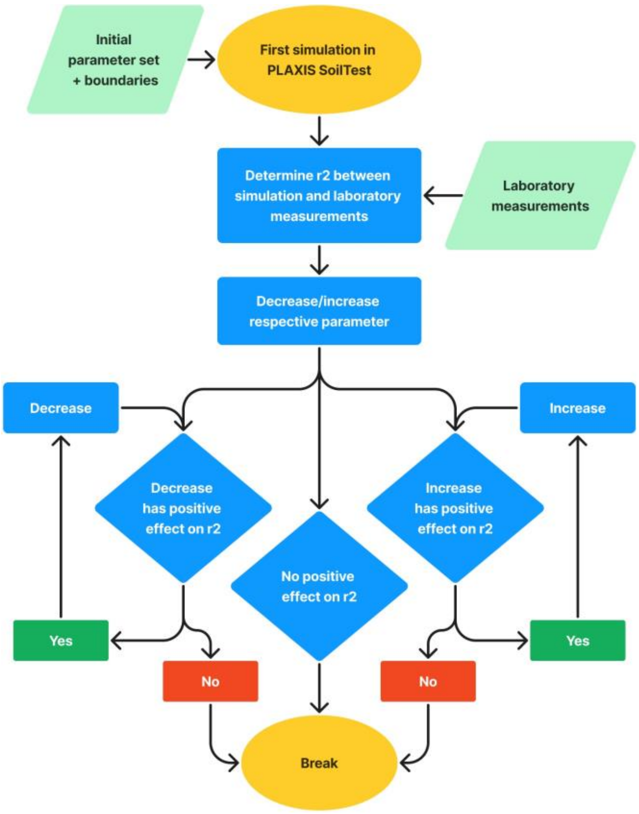

Figure 2. Schematic overview of the algorithm.

Individually matching the stress-strain curve resulted in a singularity, meaning that the parameter set after optimisation could be very different depending on the initial parameter set or optimisation order, which is why an additional feature needed to be fitted simultaneously. The selected additional feature was the ε_{vol}-ε_{ax} for the drained tests and the u_{excess}-ε_{ax} for the undrained tests. After the optimisation the stress-strain curves matched significantly better, an example of an optimised curve is shown in Figure 3.

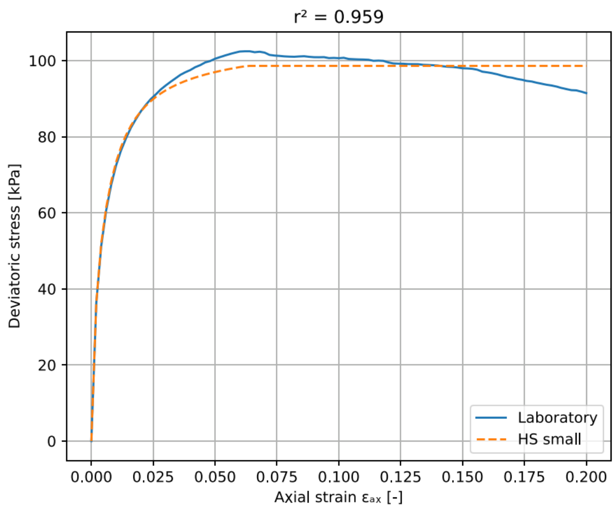

Figure 3. Example of comparison of triaxial test simulation with the optimised parameter set (HS small with measurement (Laboratory)).

3 RESULTS AND DISCUSSION

The optimisation algorithm has been deployed for 3073 tests in total. The tests are subdivided in categories based on the main soil type classification available in the text file. It is important to note that the soil type given does not mean that it only consists of this specific soil. Descriptions in the text file are often quite long (and subjective), E.g. "CLAY= slightly silty = slightly organic grey". In this example, the sample is labelled as clay since this is the main component. The optimisation results for all 3073 tests are presented in Table 1 and Figure 4, the left graph shows the r^2 of the initial parameter set an the right graph shows the r^2 of the optimised parameter set. The median r^2 of the comparison between the simulated triaxial test and the measurement improved significantly when the optimised parameter set was used. Softer soils like clay and peat showed a better performance in terms of r^2 than sand and silt. The poorer performance for sand and silt can be explained due to limitations of the HS small model. Sand and silt sometimes show a high peak strength and low residual strength, this softening behaviour cannot be captured by the HS small model.

Table 1. Optimisation results (median r^2).

Soil [-]	Quantity [-]	Initial r^2 [-]	Optimised r^2 [-]
Clay	1707	-0.51	0.92
Sand	718	0.36	0.71
Peat	374	0.55	0.99
Silt	274	-5.39	0.09

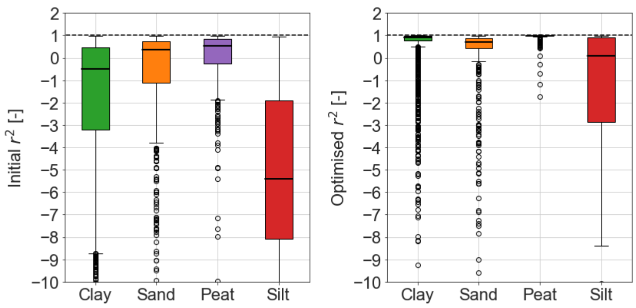

Figure 4. Results in terms of r^2 of comparison between simulated and measured stress-strain path for initial parameters set (left) and optimised parameter set (right).

The results of the optimisation are stored in a database which consist of soil properties, soil parameters and optimised model parameters. The soil properties are relatively easy to obtain. For this reason data analysis techniques have been used to predict soil parameters and optimised model parameters based on soil properties.

The soil properties $(\gamma, w, \gamma_d, e_0 \text{ and } n)$ showed a strong correlation with 5 parameters, the soil parameter φ' and the optimised model parameters

E_{50}^{ref}, E_{oed}^{ref}, E_{ur}^{ref} and G_0^{ref}. The single linear/-exponential regression managed to find a fit with an r^2 > 0.4 for these parameters. Still, a lot of scatter in the graphs was noticed which is why more advanced machine learning methods were explored. The machine learning models: Multiple Linear Regression (MLR) Artificial Neural Network (ANN), Gradient Boosting (GBR) and Kernel Ridge Regression (KRR) were selected based on an initial analysis on the data set, and a literature study in which similar models were used. Different input sets were presented to the machine learning model, input set 1 only consisted of the soil type (s) as classified in the laboratory, every successive input set added a soil property in the same order as mentioned above. The soil parameters and optimised model parameters are the output. After training, the machine learning models were able to make significant better predictions for the same 5 parameters, with an increase of r^2 in the range of 0.05-0.27 (average of 0.2), compared to the single linear/exponential regression methods. Providing the machine learning models with more soil properties generally resulted in an increase in performance. An example for the prediction of the E_{ur}^{ref} is presented in Figure 5, where the x-axis shows the different Machine learning models, the y-axis the input sets and the z-axis the r^2 score. All the results were evaluated using (group)k-fold.

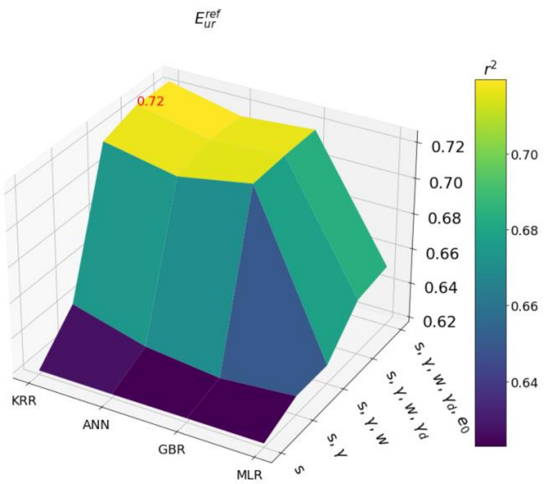

Figure 5. Machine learning prediction result.

4 CONCLUSIONS

This paper presents methods to provide guidance in the parameter determination, optimisation and selection for the HS small model parameters.

An initial parameter set was derived by expanding upon the soil parameters (traditional method). This resulted in relatively poor results when comparing the stress-strain curve of the simulation to that of the measured one in the laboratory. It is therefore concluded that the traditional method could only be used as a first estimate to determine the model parameters.

The developed optimisation algorithm was deployed for all triaxial tests and a significant improvement in r^2 was observed, the median r^2 increased from -0.61 to 0.81. The developed algorithm can optimise the initial HS small parameter sets, by matching the simulated/calculated stress-strain curve.

The trained machine learning models, could be used to select the soil parameter φ' and the optimised HS small model parameters E_{50}^{ref}, E_{oed}^{ref}, E_{ur}^{ref} and G_0^{ref} with an r^2 in the range of 0.6-0.74 by using 1 to 5 soil properties as input parameters in the ML algorithm. The linear/exponential regression results come in the form of equations that can also be used, and they may even be easier to apply, but these have a significantly lower r^2 score in the range of 0.41-0.56.

It is important to note that these methods, results and conclusions are based on triaxial test and have not been validated for other tests and engineering practices.

ACKNOWLEDGEMENTS

Authors would like to thank Dr. Ir. M.A. Cabrera and Dr. Ir. G. Rongier of TU Delft for their input.

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