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Applying machine learning to the development of surrogate models for shafts in clay

Application de l'apprentissage automatique au développement de modèles de substitution pour les puits dans l'argile

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ABSTRACT: Surrogate models are machine learning-based models that approximate aspects of interest of a reference numerical model while being considerably faster to run. This feature makes them very attractive for engineering purposes, such as design optimisation and back-analysis. A surrogate model capable of predicting the short-term vertical movements around a shaft excavated in clay is developed in this paper. The surrogate model consists of an artificial neural network (ANN) which is trained with an extensive database generated from a finite element (FE) model considering variations in shaft geometry (diameter and depth). Correspondingly, the ANN is established to predicting the surface and subsurface vertical displacements around the structure for a given shaft geometry. The procedure followed for handling the data inputs as well as optimising the training of the ANN is described. Furthermore, the predictive capabilities of the ANN are thoroughly assessed against the numerically-generated data demonstrating an overall excellent performance. This suggests that the FE model of the shaft can be confidently replaced by the ANN in preliminary design stages.

RÉSUMÉ: Les modèles de substitution sont des modèles basés sur l'apprentissage automatique qui se rapprochent des aspects intéressants d'un modèle numérique de référence tout en étant considérablement plus rapides à exécuter. Cette caractéristique les rend très attrayants à des fins d'ingénierie, telles que l'optimisation de la conception et la rétro-analyse. Un modèle de substitution capable de prédire les mouvements verticaux à court terme autour d'un puits creusé dans l'argile est développé dans cet article. Le modèle de substitution consiste en un réseau neuronal artificiel (RNA) qui est entraîné à l'aide d'une vaste base de données générée à partir d'un modèle d'éléments finis (EF) prenant en compte les variations de la géométrie du puits (diamètre et profondeur). En conséquence, le RNA est réglé pour prédire les déplacements verticaux de surface et de subsurface autour de la structure pour une géométrie du puits donnée. La procédure suivie pour traiter les données d'entrée et optimiser l'entraînement de le RNA est décrite. Les capacités prédictives de le RNA sont minutieusement évaluées par rapport aux données générées numériquement, ce qui démontre une excellente performance globale. Cela suggère que le modèle EF du puits peut être remplacé en toute confiance par le RNA dans les étapes préliminaires de la conception.

Keywords: Shafts; excavations; machine learning; surrogate modelling; artificial intelligence.

1 INTRODUCTION

Surrogate models, or meta-models, present several potential advantages in engineering design due to their fast evaluation, rendering them particularly suitable for back-analysis (Ferrero et al., 2023) or design optimisation. In this paper, a surrogate model is proposed as a pre-design tool for estimating ground movements due to shaft excavation in London Clay. Typically, these are evaluated based on empirical expressions established from limited field data (New and Bowers, 1994) and their performance is often limited to geometries similar to those employed in case histories. This severely limits their applicability to new infrastructure where a range of possible geometries may be considered throughout the various design stages. Alternatively, detailed finite element analyses can be performed, although their accuracy is highly dependent on the material models used and the available information for their effective calibration.

Surrogate models, established based on datasets obtained from detailed finite element modelling offer a third approach, combining the ease of use and fast evaluation of empirical expressions with the physics-based accuracy typical of numerical models. This is of relevance to early design stages where ground characterisation and a detailed construction sequence are generally unavailable and thus simplifications introduced by the use of surrogate models are comparatively less important. This paper presents the procedure followed to establish a surrogate model capable of predicting ground vertical displacements due to shaft excavation in London Clay for a wide range of shaft geometries with an accuracy comparable to that of detailed finite element simulations of this problem.

2 REFERENCE NUMERICAL MODEL

The generation of a surrogate model requires detailed numerical analysis of several variants of a given structure. This can, for example, consist of different soil parameters in the case of using surrogates in the context of back analysis of a well-defined structure (Ferrero et al., 2023). In the present case, the stratigraphy and the material parameters were assumed to be known, while the geometry of the shaft was allowed to vary within pre-defined limits (see Section 3.1). Therefore, PLAXIS 2D's Python API had to be employed in order to generate, calculate and post-process axisymmetric finite element models where the geometry of a typical shaft was defined parametrically in terms of its diameter, D, and depth, H.

An idealisation of the stratigraphy typically encountered in London was assumed, with $2\,m$ of Made Ground ($\gamma = 18\ kN/m^3$, $K_0 = 0.5$, linear elastic stiffness with $E = 10\ MPa, \nu = 0.2$, strength defined by the Mohr-Coulomb failure criterion with $\phi = 30°, c = 0\ kPa$ and non-associated plasticity with $\psi = 0°$), overlying a deep layer of London Clay ($\gamma_{sat} = 20\ kN/m^3$, K_0 varying with depth identical to that used in Sailer et al. (2019)). A hydrostatic initial pore water pressure profile with the groundwater table positioned at the top of London Clay was adopted. The behaviour of the latter was modelled using the IC MAGE M01 model (Taborda et al., 2023b), which combines a non-associated Mohr-Coulomb failure criterion ($\phi = 25°, c = 5\ kPa, \psi = 12.5°$) with cyclic non-linear elasticity to describe the highly non-linear variation of stiffness with stress and strain levels. The parameters adopted for this component of the constitutive model are identical to those proposed in Sailer et al. (2019), and are briefly outlined in Table 1. A value of $p'_{ref} = 100\ kPa$ is assumed throughout. Lastly, the anisotropic permeability of London Clay ($k_h = 2 \cdot k_v$) was described using the following expression, implemented as a User-Defined Flow Model in PLAXIS (Taborda et al., 2023a) and calibrated based on data by Hight et al. (2007):

$$log_{10}\, k_v = 0.0215 \cdot (y + 2) - 9.427 \qquad (1)$$

where y is the vertical coordinate ($y = 0\ m$ denotes the ground surface), and k_v and k_h are the vertical and horizontal permeabilities in m/s, respectively.

Table 1. Stiffness properties for London Clay.

Shear stiffness		**Bulk stiffness**	
G_{ref}	$51.7\ MPa$	K_{ref}	$26.7\ MPa$
a	5.6×10^{-5}	r	1.27×10^{-4}
b	0.9	s	1.8
$R_{G,min}$	0.0645	$R_{K,min}$	0.13275
G_{min}	$2.67\ MPa$	K_{min}	$5\ MPa$

The excavation of the shaft (with diameter D and depth H) was simulated in $1\ m$ steps, with each ring being built concurrently with the next excavation (i.e. the support trailed the excavation by one step). The duration for each excavation stage was, for simplicity, set to $D/10$ days. For the top half of the shaft, pre-cast concrete segments ($E = 37\ GPa$, $\nu = 0.2$) were adopted for support, while sprayed concrete was used in the lower half. For both cases, a thickness of $0.35\ m$ was assumed based on typical geometries of shafts built in London. The mechanical behaviour of the shotcrete support was simulated using the IC MAGE M07 model (Taborda et al., 2023c), which introduces a time-dependent Young's modulus following the expression proposed by the CEB-FIP Model Code 90 (CEB-FIP, 1993) with $E_{28} = 30\ GPa, s = 0.25$ and $\nu = 0.2$. The interaction between the support and the soil was modelled using interface elements with their strength reduced to two thirds of that of the soil ($c_{int}/c_{soil} = \tan\phi_{int} / \tan\phi_{soil} = 2/3$), and normal and tangential stiffness values of $10^6\ kN/m^3$.

3 SURROGATE MODEL

In this study, the numerical model described in Section 2 was surrogated with an artificial neural network (ANN) from the deep learning framework *Keras* (Chollet et al., 2015). The ANN was trained, using synthetically generated data, to predict the surface and subsurface settlement from an input shaft geometry. The procedures followed in the creation of the surrogate model including data generation, training of the ANN and its evaluation are described subsequently.

3.1 Synthetic database

A synthetic database of numerical analyses, for different shaft geometries, was generated using the numerical model described above; the database comprised a total of 100 analyses.

The Latin Hypercube Sampling (LHS) method (McKay et al., 1979) was employed to define the combined shaft depth and diameter for each of the *samples* (analyses) in the database. In simple terms, the LHS generalises the concept of a latin square, i.e. a square grid of equally-spaced intervals where only one sample point is located in each row and column of the grid, to arbitrary input dimensions. Bounds for the input parameters are required by the LHS and these were taken as 2.5 m and 20 m for the shaft diameter and 20 m and 70 m for the shaft depth. These bounds were aimed to cover a large portion of the shaft geometries to be potentially constructed in London.

Displacement troughs from the end of the excavation were extracted from the analysis results at interval depths corresponding to $0.1H$ (where H is the shaft depth), from the surface to the base of the shaft. Correspondingly, 11 curves were produced per analysis. Each of these curves extended radially from 0.1 m to $2H$ and included 201 equally-spaced points. Note that the movement of the points located at the shaft boundary can be largely affected by the presence of the interface element, hence it was decided to shift the starting point of the troughs 0.1 m away from the boundary.

3.2 Training procedure

The synthetic dataset was divided into the training (70%), validation (10%) and testing (20%) datasets. The validation dataset was employed to assess the generalisation ability of the ANN model at the model tuning stage; the performance of the ANN, adopting its final configuration, was evaluated against the testing dataset. The ANN was trained to predict the ground displacement given the following input variables: shaft depth (H) and diameter (D), the ratio z/H (where z is the depth of the point to be evaluated) and the ratio x/H (where x is the radial distance from the point to the shaft boundary). To ensure that all the input variables were in the same scale prior to training of the model, they were normalised by the maximum absolute value of each variable found in the training dataset.

The ANN adopted a feedforward architecture, the *adam* optimiser (Chollet et al., 2015) and the rectified linear unit activation function for all hidden layers. The number of hidden layers, the number of neurons for each hidden layer and the learning rate were fine-tuned through exploration of a large number of combinations of the abovementioned hyperparameters. A summary of the hyperparameters adopted by the ANN is presented in Table 2.

Table 2. Summary of hyperparameters adopted by the ANN.

Hyperparameter	Value
Hidden layers	{640,704,832,320,576,864,288}
Activation function	Relu
Optimiser	Adam
Learning rate	$3.747 \cdot 10^{-5}$

3.3 Performance evaluation

Figure 1 and Figure 2 depict regression plots where the displacement predicted by the surrogate model is plotted in the vertical axis against the actual displacement (i.e. that obtained numerically) for the training and testing datasets, respectively. Note that negative displacements indicate settlement of the ground. The solid black line signifies a perfect agreement between predictions and target values. It can be seen that data points generally plot in a narrow band around the black line which illustrates the overall excellent performance of the surrogate. In quantitative terms, the coefficient of determination (R^2), which yields a value of 1 when the residual between observations and predictions is zero, was obtained as 0.998 and 0.996 for the training and testing datasets, respectively. Similarly, the Mean Absolute Error (MAE) was determined as $6.7 \cdot 10^{-5}$ m and $9.5 \cdot 10^{-5}$ m for the two datasets.

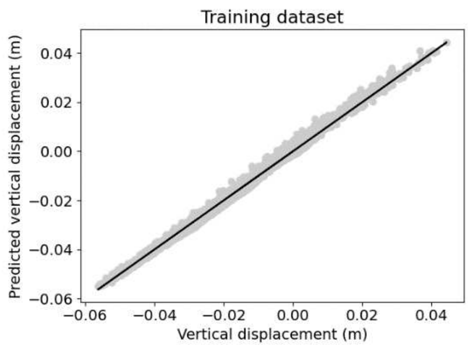

Figure 1. Regression plot of the training dataset.

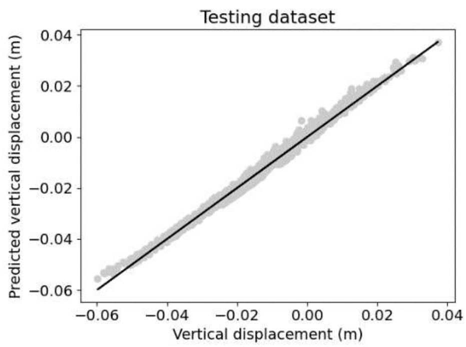

Figure 2. Regression plot of the testing dataset.

Figure 3 shows the displacement troughs at depths ranging from 0 m to depth H for a shaft of 10.1 m diameter and 36 m depth, part of the database described in Section 3.1. The troughs from the numerical data are shown according to the data split (training, testing and validation) they belonged to. According to the numerical analyses, the settlement magnitudes reduce gradually with depth such that for z/H larger than about 0.6 there is heave next to the shaft. It can be observed that the surrogate model is capable of reproducing that trend as well as the shape of the displacement troughs at different depths. Overall, the results demonstrate that the surrogate model can be used with confidence for the prediction of ground movements around a newly constructed shaft. It is useful to note that while each of the numerical analyses described in this paper took several hours to complete, the surrogate model can make predictions almost instantaneously, allowing for quick estimates in the early design stages.

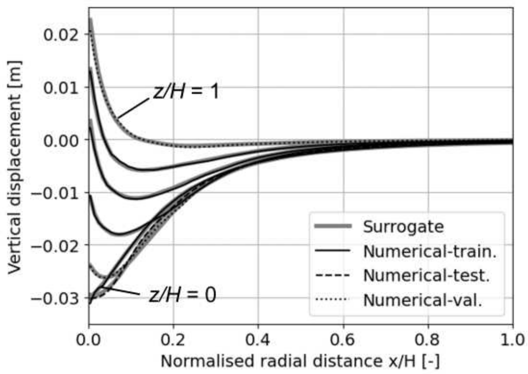

Figure 3. Settlement troughs at different depths for a shaft of 10.1 m diameter and 36 m depth.

4 CONCLUSIONS

A dataset consisting of vertical movements due to shaft excavation in London Clay was created for a wide range of geometries by performing detailed coupled consolidation axi-symmetric finite element analyses. The obtained data were subsequently used to create a surrogate model using an ANN, which was shown to reproduce with a high level of accuracy the numerical data. This work paves the way for greater adoption of this type of data-centric models in the pre-design of geotechnical structures.

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REFERENCES

CEB-FIP (1993). CEB-FIP Model Code 90. Thomas Telford, London.

Chollet, F., & others. (2015). Keras. GitHub. Retrieved from https://github.com/fchollet/keras.

Ferrero, J. A., Ruiz Lopez, A., Taborda, D. M. G., Brasile, S. (2023) Applying the observational method to a deep braced excavation using an artificial neural network. *Proceedings of the 10th European Conference on Numerical Methods in Geotechnical Engineering*, London, UK. http://doi.org/10.53243/NUMGE2023-303.

Hight, D. W., Gasparre, A., Nishimura, S., Minh, N. A., Jardine, R. J., Coop, M. R. (2007) Characteristics of the London Clay from the Terminal 5 site at Heathrow Airport, *Géotechnique*, 57(1), pp. 3-18. http://doi.org/10.1680/geot.2007.57.1.3.

McKay, M. D. Beckman, R. J. Conover, W. J. (1979) A Comparison of Three Methods for Selecting Values of Input Variables in the Analysis of Output from a Computer Code, *Technometrics*, 21 (2), pp. 239-245. http://doi.org/10.1080/00401706.2000.10485979.

New, B. M., Bowers, K. H. (1994) Ground movement validation at the Heathrow Express trial tunnel. *Proceedings of the 7th international symposium Tunnelling '94*, Boston, MA, pp. 301-329.

Sailer, E., Taborda, D. M. G., Zdravkovic, L., Potts, D. M. (2019) Fundamentals of the coupled thermo-hydro-mechanical behaviour of thermo-active retaining walls. *Computers and Geotechnics*, 109, pp. 189-203. http://doi.org/10.1016/j.compgeo.2019.01.017.

Taborda, D. M. G., Kontoe, S. & Tsiampousi, A. (2023a) IC MAGE Flow Model 01 – Nonlinearly varying anisotropic permeability (Version 1.0). *Zenodo*. http://doi.org/10.5281/zenodo.7796383.

Taborda, D. M. G., Kontoe, S. & Tsiampousi, A. (2023b) IC MAGE Model 01 – Strain hardening /softening Mohr-Coulomb failure criterion with isotropic small strain stiffness (Version 2.1). *Zenodo*. http://doi.org/10.5281/zenodo.8239422.

Taborda, D. M. G., Kontoe, S. & Tsiampousi, A. (2023c) IC MAGE Model 07 – Simple non-linear time-dependent stiffness model for concrete (Version 1.4). *Zenodo*. http://doi.org/10.5281/zenodo.8234140.