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Applying the observational method to a deep braced excavation using an artificial neural network

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ABSTRACT: The Observational Method (OM) has long been used in Geotechnical Engineering, and its benefits have been demonstrated in several real cases. However, it has not been widely adopted among practising engineers. There are several reasons for it, some are related to contractual issues and risk sharing between stakeholders, but others are related to technical problems that jeopardise a smooth and successful implementation from an engineering perspective. This paper proposes a framework to implement the OM through machine learning and optimisation algorithms, developing Artificial Neural Network (ANN) models to act as quick-to-evaluate surrogate models coupled with a Genetic Algorithm (GA) to carry out the respective back analyses. The framework is demonstrated through a case study, showing how it can be used to determine soil parameters unambiguously and provides a systematic approach for implementing the OM. The procedure presented enhances the design and construction of geotechnical structures, supporting a more sustainable development within the geotechnical engineering industry.

Keywords: Machine Learning; Observational Method; Braced Excavations; Surrogate Model; Artificial Neural Network,

1 INTRODUCTION

Traditional design methodologies commonly used in the geotechnical engineering industry can lead to costly and non-environmentally friendly solutions due to the inherently conservative assumptions involved. It is also known that the biggest challenge faced by the newer generations of engineers is the climate emergency. The Observational Method (OM) (Peck, 1969) provides a framework that allows efficient design solutions to be produced by taking advantage of field observations made during construction. A complete and detailed description of the OM can be found in Gaba et al. (2017) and Hardy et al. (2018), while a comprehensive list of projects that have implemented the OM can be found in Powderham & O'Brien (2020).

Numerical analysis is now established as a commonly adopted tool in geotechnical design as it offers unparalleled capabilities for predicting the response of geotechnical structures, thanks in part to the sophisticated soil constitutive models it adopts. However, despite the significant progress made, the standard procedure for calibrating the parameters of soil constitutive models from limited laboratory and in-situ testing data and then using those parameters in numerical analysis to predict the behaviour of geotechnical structures has not always been successful (Hashash et al., 2006). Within the context of the OM, the predicting capabilities of numerical models can be enhanced by re-evaluating the soil parameters once field observations become available during construction and the improved numerical model can then be used to make new predictions of future construction stages. This process invariably requires back analyses to find the set of soil parameters that provides the best match with the field observations. While optimisation methods such as genetic algorithms enable the back analysis procedure to be automated, they require performing a large number of numerical analyses and can therefore be very computationally expensive. The use of a surrogate model able to approximate the behaviour of the numerical model during the optimisation procedure emerges as an interesting alternative in order to streamline the process of back analysis and of the OM as a whole. This paper proposes a new framework to implement the OM for braced excavations through the use of surrogate models and optimisation algorithms to carry out the required back analyses, demonstrating its potential by applying it to a case study of an excavation in Central London.

2 SELECTED CASE STUDY

2.1 *Description of the problem*

A deep excavation in Central London, for which detailed descriptions in terms of ground conditions, construction sequence and monitoring data are available in

Wood & Perrin (1984a) and Wood & Perrin (1984b), will be used herein to demonstrate the application of the proposed framework based on machine learning and global optimisation algorithms. This excavation had dimensions in plan of approximately 100 m by 60 m and 11.4 m of depth. The 800 mm thick and 18 m deep diaphragm wall was supported during excavation by three levels of steel frames supported by concrete soldier piles. The permanent structure included a 1.5 m thick foundation slab and three 350 mm reinforced concrete slabs. The construction sequence, as described in Sailer et al. (2019), is listed in Table 1.

In terms of ground conditions, the stratigraphy, illustrated in Figure 1, included 4.8 m of made ground, 2.0 m of terrace gravel deposits, 40 m of London clay, 12.0 m of Lambeth group clay and 7.0 m of Thanet sand, overlying chalk. The water table was located at a depth of 4.0 m, while that corresponding to the lower aquifer was assumed to be, at the time of construction, at the interface between the Lambeth group clay and the Thanet sands (Sailer et al., 2019).

Table 1. Construction sequence

Phase	Description
0	Stress initialisation
1	Construction of diaphragm wall
2	Excavate to +18 mOD (45 days)
3	Install prop level 1 (+19.5 mOD) (50kN/m of pre-stress)
4	Dewater terrace gravel deposits
5	Excavate to +15 mOD (30 days)
6	Install prop level 2 (+16.2 mOD) (80 kN/m of pre-stress)
7	Excavate to +12.5 mOD (90 days)
8	Install prop level 3 (+13.0 mOD)
9	Excavate to +10.6 mOD (60 days)
10	Construct base slab (30 days)
11	Remove prop level 3
12	Construct slab level 3 (+15.3 mOD, 30 days) (120 kN/m of pre-stress)
13	Remove prop level 2
14	Construct slab level 2 (+18.8 mOD, 30 days)
15	Remove prop level 1
16	Construct slab level 1 (+22.0 mOD, 30 days)

2.2 Numerical analysis

This excavation was simulated with a finite element (FE) model assuming plane-strain conditions using PLAXIS 2D (Bentley Systems, 2022). The strength of all the materials considered in the analysis was modelled using a non-associated Mohr-Coulomb failure criterion, with parameters adopted from Sailer et al. (2019) and listed in Table 2. In terms of stiffness, with the exception of made ground, which was modelled as linear elastic, all materials were simulated as non-linear elastic, with the shear and bulk moduli being given by a modified hyperbolic relationship as proposed in Taborda et al. (2016):

$$G_{tan} = G_{ref} \cdot \left(\frac{p'}{p'_{ref}}\right) \cdot \left(R_G + \frac{1-R_G}{1+\left(\frac{E_d}{a}\right)^b}\right) \quad (1)$$

$$K_{tan} = K_{ref} \cdot \left(\frac{p'}{p'_{ref}}\right) \cdot \left(R_K + \frac{1-R_K}{1+\left(\frac{|\varepsilon_{vol}|}{r}\right)^s}\right) \quad (2)$$

where p'_{ref} = 101.3 kPa, E_d is the generalised deviatoric strain and ε_{vol} is the volumetric strain. The relationships above were implemented as a user-defined soil model (UDSM) for PLAXIS (Bentley Systems, 2022), as detailed in Taborda et al. (2022a), integrated using a modified Euler scheme with automatic substepping and error control, as proposed by Sloan et al. (2001) and outlined in Taborda et al. (2022b). The values of the various parameters were obtained from Sailer et al. (2019) and are listed in Table 2. The initialisation of the ground stresses was performed assuming unit weights of 18.0 kN/m^3 for made ground and 20.0 kN/m^3 for all other materials. The at-rest coefficient of earth pressure, K_0, was assumed to be 0.5 for made ground and terrace gravel deposits, and 1.0 for Lambeth group clay and Thanet sand. For the London clay, K_0 = 1.5 for the top 10 m, 1.25 for the subsequent 10 m and finally 1.0 for the remaining depth.

Table 2. Adopted material properties (Sailer et al., 2019)

Material	Properties
Made ground	ϕ = 30°, ψ = 0°, c = 0 kPa, E = 10 MPa, ν = 0.2
Terrace gravel deposits	ϕ = 35°, ψ = 17.5°, c = 0 kPa, G_{ref} = 41.9 MPa, a = 1.45E-4, b = 1.00, R_G = 0.03511, K_{ref} = 49.8 MPa, r = 2.47E-4, s = 1.25, R_K = 0.15440
London clay	ϕ = 25°, ψ = 12.5°, c = 5 kPa G_{ref} = 51.7 MPa, a = 5.60E-5, b = 0.90, R_G = 0.06450, K_{ref} = 26.7 MPa, r = 1.27E-4, s = 1.80, R_K = 0.13275
Lambeth group clay	ϕ = 27°, ψ = 13.5°, c = 25 kPa G_{ref} = 51.9 MPa, a = 1.10E-4, b = 0.95, R_G = 0.04662, K_{ref} = 61.3 MPa, r = 6.50E-5, s = 1.40, R_K = 0.07589
Thanet sand	ϕ = 40°, ψ = 20°, c = 0 kPa G_{ref} = 65.3 MPa, a = 4.60E-5, b = 0.85, R_G = 0.02631, K_{ref} = 29.8 MPa, r = 1.55E-4, s = 1.10, R_K = 0.27947

Given that coupled hydromechanical analyses were performed, the permeability of the materials needs to be characterised. For the drained materials (made ground, terrace gravel deposits and Thanet sands), a sufficiently large value was specified, while for the undrained materials a linear reduction with depth of the logarithm of permeability was adopted. This was introduced in the analysis by using a user-defined flow model (UDFM), following the approach outlined in Bui et al. (2019). The relationship adopted was based on the data presented by Hight et al. (2007): $\log_{10}k = -9.46-0.02z$, where z is the distance to the top of London clay and k is the permeability in m/s. Figure 1 shows the underdrained porewater pressure and K_0 profile resulting from the previously identified site conditions.

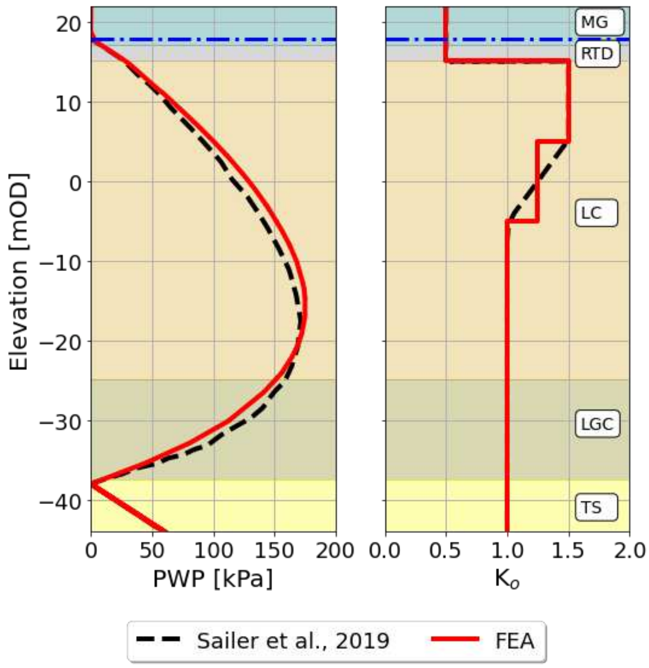

Figure 1. Stratigraphy, pore water pressure and K_0 profile

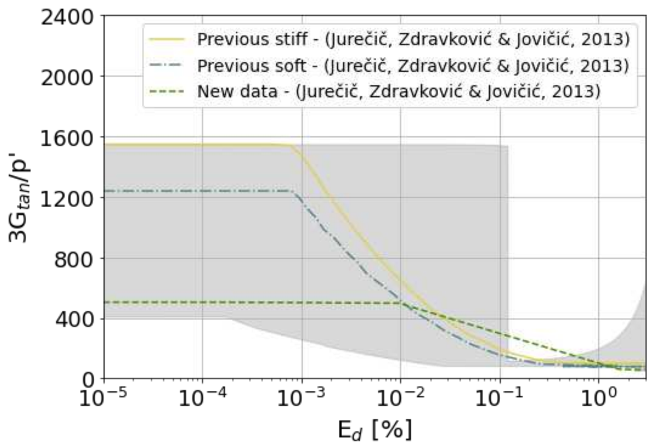

Figure 2. Boundaries adopted for the normalised tangent shear stiffness of London Clay compared with data available in the technical literature.

3 SURROGATE MODELLING

As described by Forrester et al. (2008), optimisation algorithms can be deployed directly to numerical simulations. However, the latter tend to have long running times and so their use becomes inefficient. Instead, surrogate (or meta) models can be adopted: these are mathematical approximations of the numerical simulations and run considerably faster than the numerical models they approximate. In this research, Artificial Neural Networks (ANNs) were used as surrogate models approximating the behaviour of the FE model described in Section 2.2. The ANNs were trained with data generated from the numerical models and subsequently coupled with an optimisation algorithm to perform the back analysis of the described deep excavation. For the development of the surrogate model, two different FE models were built. The first is denoted as low-fidelity model as it adopted several simplifications: a relatively coarse mesh using 6-noded triangular elements (instead of the more accurate 15-noded triangular elements) was adopted and the analyses were performed as undrained rather than considering coupled-flow deformation. This model was used for the purpose of providing a computationally 'cheap-to-run' model to enable a detailed study of the development of ANN surrogate models for braced excavations, specifically to establish the size of the database and the data handling procedure for the surrogate training. Once the structure of the database had been determined, a second high-fidelity model was created without the simplifications mentioned above to create the database for training of the surrogate model to be used in the back analysis.

The soil parameters to be back analysed were decided based on a set of sensitivity analyses which showed that the parameters defining the shear stiffness degradation of the soil (Equation 1) had the greatest influence on the wall response. Conversely, the effect of the parameters controlling the bulk stiffness (Equation 2) was found to be minor, which was unsurprising given the negligible volumetric deformation associated with the short periods considered in the coupled analysis. Therefore, these were assumed to be constant for all analysed cases. Given that London Clay is a well-studied soil, and to maintain the training and searching space within realistic values, the upper and lower bounds of the shear stiffness were taken from previously reported stiffness decay curves. The shaded region shown in Figure 2 represents the boundaries of the shear stiffness degradation curves, which were determined based on the reference curves presented by Jurečič et al. (2013). The parameters defining those boundaries are included in Table 3, with these being enforced strictly such that no sample was created violating these constraints. The Latin Hypercube Sampling (LHS) method was used to determine the parameters of each sample, ensuring an efficient coverage of the training space. Further details on the LHS method can be found in Forrester et al.

(2008), Koziel & Leifsson (2013) and Jiang et al. (2020).

Table 3. Defined upper and lower bounds for the shear modulus definition of London Clay (searching and training space)

Bound	G_{ref} (kPa)	a	b	R_G
Lower	16667	10-5	0.5	0.0
Upper	51667	10-2	2	0.4

Once both FE models were set up, and the decision variables and training/search space were defined, a comparative analysis with different database sizes and number of data points along the elevation of the wall used for each training curve was undertaken using the low-fidelity model. This exercise included the creation of five different databases comprising 75, 200, 300, 400 and 500 samples, respectively. Figure 3 shows the wall movements along its elevation at the end of excavation phase 11 for the database containing 300 samples. It can be observed that the adopted sampling space produced results covering a wide range of wall movements with most samples concentrated towards the lower limit of the interval of simulated movements.

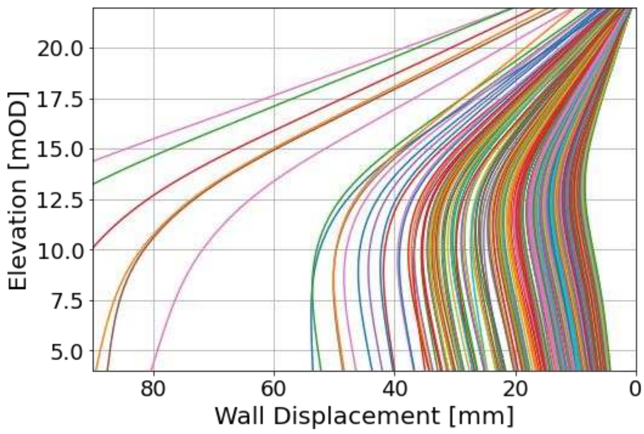

Figure 3. Wall movements obtained at the end of Phase 11 for the database with 300 samples.

The ANN training was carried out using the open-source Python library *Scikit-Learn* (Pedregosa et al., 2011). A careful exercise of hyperparameter tuning was carried out to maximise the performance of the ANN. The resulting hyperparameters are listed in Table 4. The ANN was trained with the five databases mentioned above and it was found that a minimum of 300 samples was required for the ANN predictions to be consistent with the numerical model within and outside the training range. It is worth noting that this number of samples is lower than those reported by others (e.g. Kung et al., 2007; Yong et al., 2022) for similar applications. The influence of varying the number of points along the elevation of the wall used for training was also investigated and a total of 144 points was found to be optimal. Furthermore, the ANN was trained individually for each excavation phase as this improved the performance significantly when compared to the alternative process where the excavation phase was included as an input variable. The data structure was then adopted to train the ANN models based on synthetically generated data from the high-fidelity FE model. Figure 4 shows the comparison between the predictions of the ANN and the high-fidelity model at the end of phase 7 for four sets of input parameters not considered in the training nor the testing datasets, it can be observed that the ANN showed an excellent agreement with the numerical results.

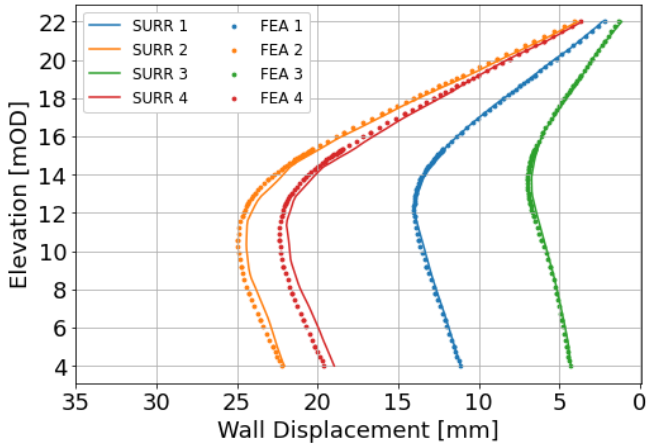

Figure 4. ANN performance check comparing the phase 7 wall displacement predictions through FE and surrogate models for four different input sets (excluded from the training and testing data sets).

Table 4. ANN hyperparameters

Hyperparameter	Value
Activation function	*relu*
Number of hidden layers	6
Neurons per layer	375-500
Initial learning rate	0.001
Learning rate	*constant*
Solver	*adam*

4 BACKANALYSIS AND FORWARD PREDICTION

As part of this research and to investigate the application of ANN in the context of the observational method, the following two back analysis strategies were adopted:

- An independent back analysis for each excavation phase to determine whether the optimal soil parameters for each excavation phase could be found within the training and search spaces.
- A back analysis for each excavation phase to obtain the soil parameters matching the measured behaviour for all previous phases combined. This back analysis strategy was deemed most relevant for practical scenarios as it enables predictions of subsequent excavation

phases to be made using the optimal soil parameters up to that phase.

The back analysis of soil parameters is essentially an optimisation problem that consists of finding the combination of parameters that provide the most accurate model prediction when compared against field measurements. Meta-heuristic and evolutionary algorithms (Zhang et al., 2009) are well-suited tools for solving the optimisation problem as they enable the search for optimal parameters to be automated and guarantee that an objective solution is obtained. In this research, a Genetic Algorithm (GA) was adopted along with the ANN models trained in Section 3, the adopted parameters for the GA are summarised in Table 5. Further details on GA can be found in Holland (1975), Goldberg (1989), Bozorg-Haddad et al. (2017), Kramer (2017) and Mirjalili (2019).

Table 5. Parameters adopted for the Genetic Algorithm.

Parameter	**Value**
Initial population size	1000
Generation size	350
Probability of mutation	2%
Elite size	10
Maximum number of generations	250

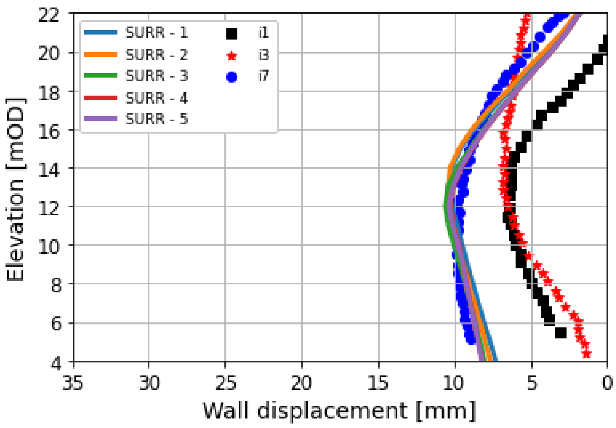

Figure 5. Predictions for Phase 7 (excavation stage) based on the back analysis of the previous phase (Phase 6, installation of second propping level).

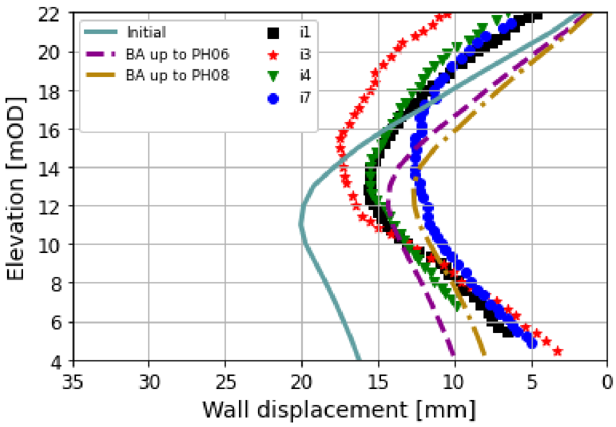

Figure 6. Predictions for Phase 11 (removal of third propping level).

The soil parameters obtained when back analysing each phase independently were within the boundaries defined, with the greatest dispersion being obtained for parameter *b*. This could be expected since *b* has the lowest influence in the non-linear degradation of G_{tan}. The results of these initial back analyses demonstrated that the combination of GA and the trained ANN models performed well and was suitable for a practical OM application using the second back analysis strategy.

It should be noted that, while in the back analyses considering each phase independently, the root-mean-square error (RMSE) was adopted to evaluate the fitness of each set of soil parameters, this metric had to be adjusted for the second series of back analyses in order to integrate appropriately the data from all previous construction phases. Moreover, it is worth noting that after everything was set up, the GA took less than 24 hours to undertake the entire back analysis.

Figure 5 and Figure 6 show a comparison between monitoring data and the forward predictions for phases 7 and 11, respectively, obtained based on the sets of soil parameters back analysed from the previous phases. Comparing the monitoring readings presented in both figures, it is noted that the movements reported for the i7 location were the highest in phase 7, but the lowest in phase 11. While the back analysis was carried out giving the same weight to the three inclinometer data sets (i1, i3 and i7), a greater weight could have been given to one of the data sets, should the aim of the back analysis have been focused on a specific sector of the excavation. Figure 6 includes the surrogate predictions using the initial soil parameters (i.e. listed in Sailer et al. (2019)), those giving the best match up to phase 6 (labelled as PH06) and those obtained up to phase 8 (labelled as PH08). It can be observed that the dispersion between the soil parameters obtained decreased when back analysing more phases as the number of potential combinations that satisfy a larger number of targets is lower. This highlights the importance of implementing robust monitoring systems that include redundancy in the layout, since larger amounts of data fed into the system ensure that the variability obtained from the back analysis is lower and that the corresponding results are more reliable. It can also be seen that the forward predictions for phase 11 using the back analysed parameters are of higher accuracy than that obtained using the initial parameters. This demonstrates further the value of the proposed framework as a way of improving predictions of future performance of structures in real-time by incorporating available monitoring data.

5 CONCLUSIONS

A new framework for the application of the OM for a braced excavation through surrogate models and optimisation algorithms is proposed in this paper. An ANN was trained as surrogate model from synthetic data generated from a FE model. Before training the final surrogate model, the use of a fast low-fidelity FE model allowed the determination of an adequate data structure for training of the ANN, the procedure yielded a requirement of a minimum of 300 samples which was noted to be lower than previously reported values for braced excavations. The ANN-based surrogate model was shown to reproduce the behaviour of the FE model with very high levels of accuracy. The practical relevance of the proposed framework was demonstrated by conducting the back analysis of soil parameters from real monitoring data combining the trained surrogate model and a GA. A similar workflow to that required by the OM was implemented allowing the optimal soil parameters up to a certain construction stage to be obtained and to make predictions for future construction stages with such parameters. It can be concluded that the coupling between surrogate modelling and optimisation algorithms offers a promising way forward for a more efficient application of the OM in braced excavations and other geotechnical structures.

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