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Developing a surrogate model for urban excavations in London

[1]Department of Civil and Environmental Engineering, Imperial College London, London, UK
[2]Seequent - The Bentley Subsurface Company, Delft, The Netherlands
yunxiang.yang22@imperial.ac.uk

Yunxiang Yang[1],
David M. G. Taborda[1],
Agustín Ruiz López[1,2],
Aikaterini Tsiampousi[1]

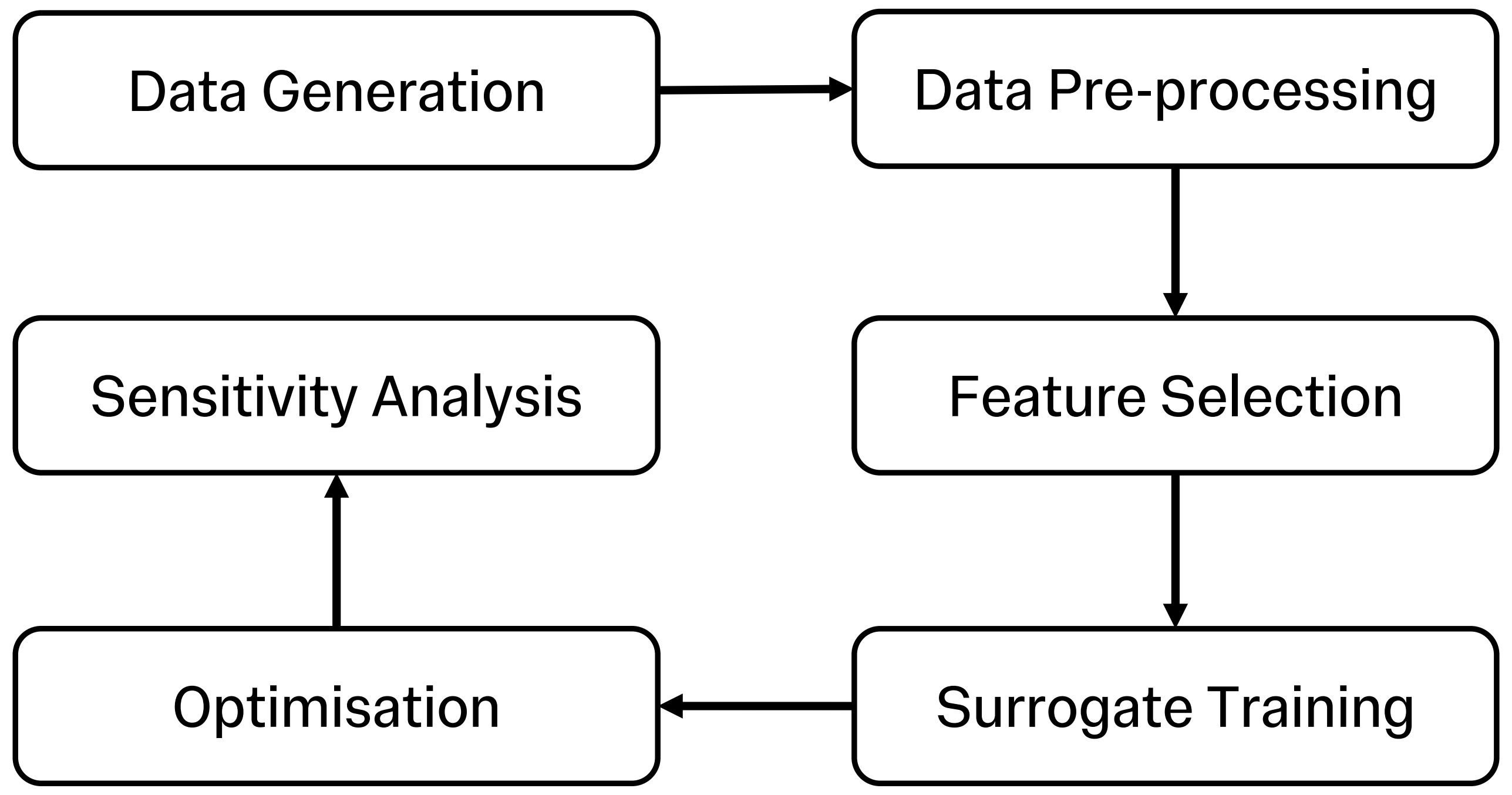
Introduction

A surrogate model, commonly referred to as meta-model, functions as an approximate mathematical representation of the desired output. These models significantly reduce computational costs compared to the original numerical models, while maintaining a high level of accuracy in their predictions. Surrogate models are commonly developed using machine learning techniques or other mathematical methodologies, offering an efficient and reliable alternative for complex simulations and analyses.

Given their ability to balance accuracy and computational efficiency, surrogate models are primarily employed to approximate the outcomes of computationally intensive simulations (Forrester et al., 2008). They are particularly valuable in tasks such as design optimisation and back-analysis, where repeat evaluations of the numerical model are necessary. Additionally, surrogate models are widely used for sensitivity analysis, enabling the examination of relationships between input features to identify potential uncertainties that may influence the desired outputs.

Stepwise development of a surrogate model

The flowchart below outlines the key steps involved in developing a surrogate model and deploying it for practical applications:



Data Generation
Data Pre-processing
Feature Selection
Surrogate Training
Optimisation
Sensitivity Analysis

Application to urban excavations

Details of the analysis

The numerical analysis involved a multi-propped urban excavation, with the diaphragm wall embedded 10 m deeper than the excavation depth and Made Ground overlaying London Clay. The mechanical behaviour of both soil layers was modelled using parameters from Sailer et al. (2019), employing the IC MAGE M01 model (Taborda et al., 2023) for London Clay, which incorporates a non-linear function for the shear and bulk moduli, coupled with a Mohr-Coulomb failure criterion. The coefficient of earth pressure at rest (K_0) profile was also adopted from Sailer et al. (2019). Initial hydraulic conditions were assumed to follow a hydrostatic water profile, with the water table positioned at the top of the London clay. The prop stiffness was set as 50 MN/m/m, with an out-of-plane spacing of 5 m. The problem was parametrised, allowing for models characterised by random combinations of a variety of geometric characteristics to be built, analysed and post-processed automatically via scripting. An example is shown in Figure 1.

Surrogate development

The database was generated using PLAXIS 2D, consisting of 100 testing analyses and 90 training analyses with varying excavation geometries. Latin Hypercube Sampling method was utilised to generate the input parameters for the analyses, including excavation depth (H: 10-50m), excavation width (W: 30-80 m), prop spacing (S_p: 3-6m), thickness of Made Ground (t_{MG}: 1-5m) and thickness of diaphragm wall (t_{DW}: 0.6-1.2 m). The obtained deformed shapes for the diaphragm wall are shown in Figure 2. An Artificial Neural Network model using *Keras* (Chollet & others, 2015), with the architecture shown in Figure 3, was adopted as the surrogate model to predict the short-term horizontal deformation behaviour of the diaphragm wall during the final stage of the excavation. This surrogate accurately replicated the numerical results, yielding a coefficient of determination R^2 of 99.56%.

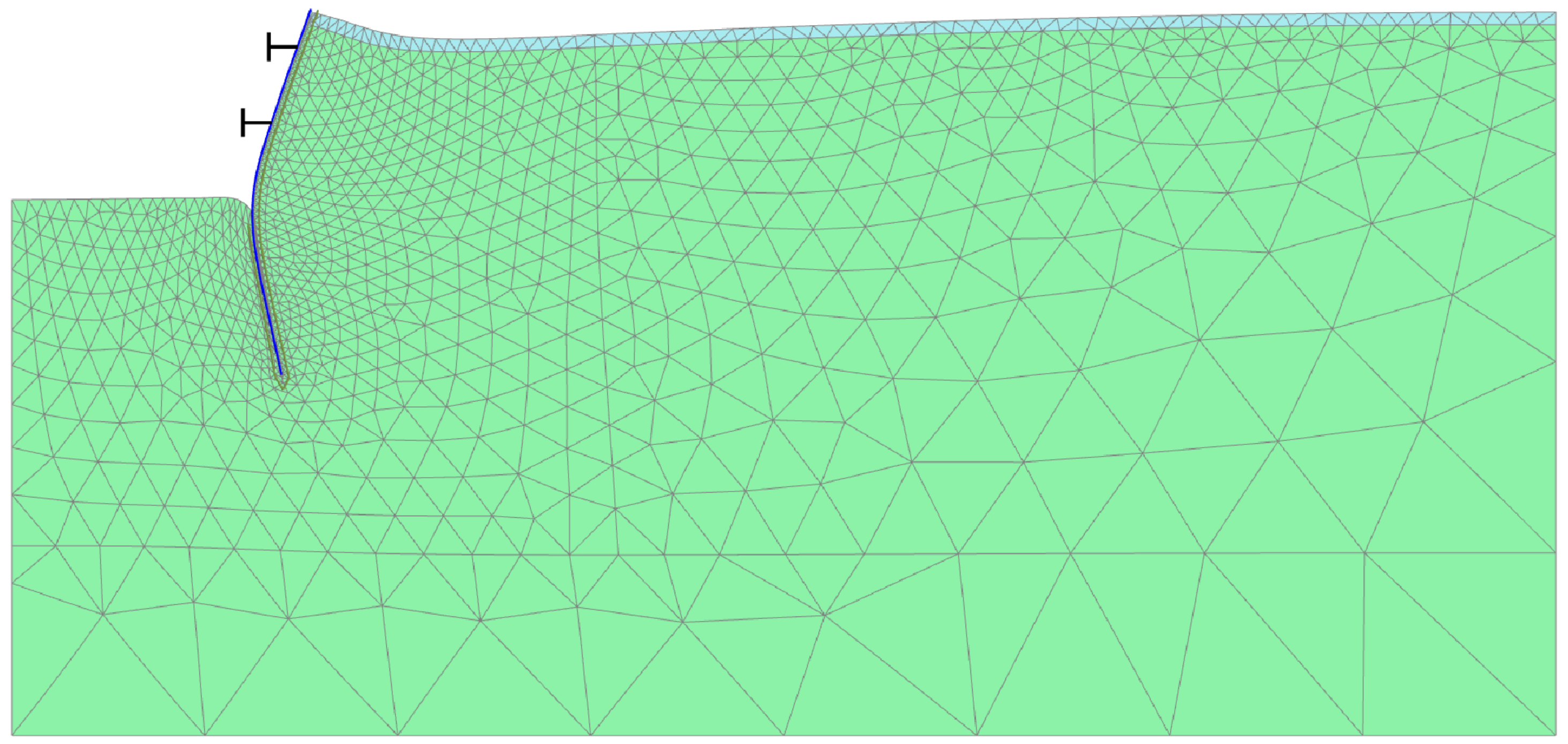


Figure 1: Deformed mesh configuration at the final stage of the numerical analysis

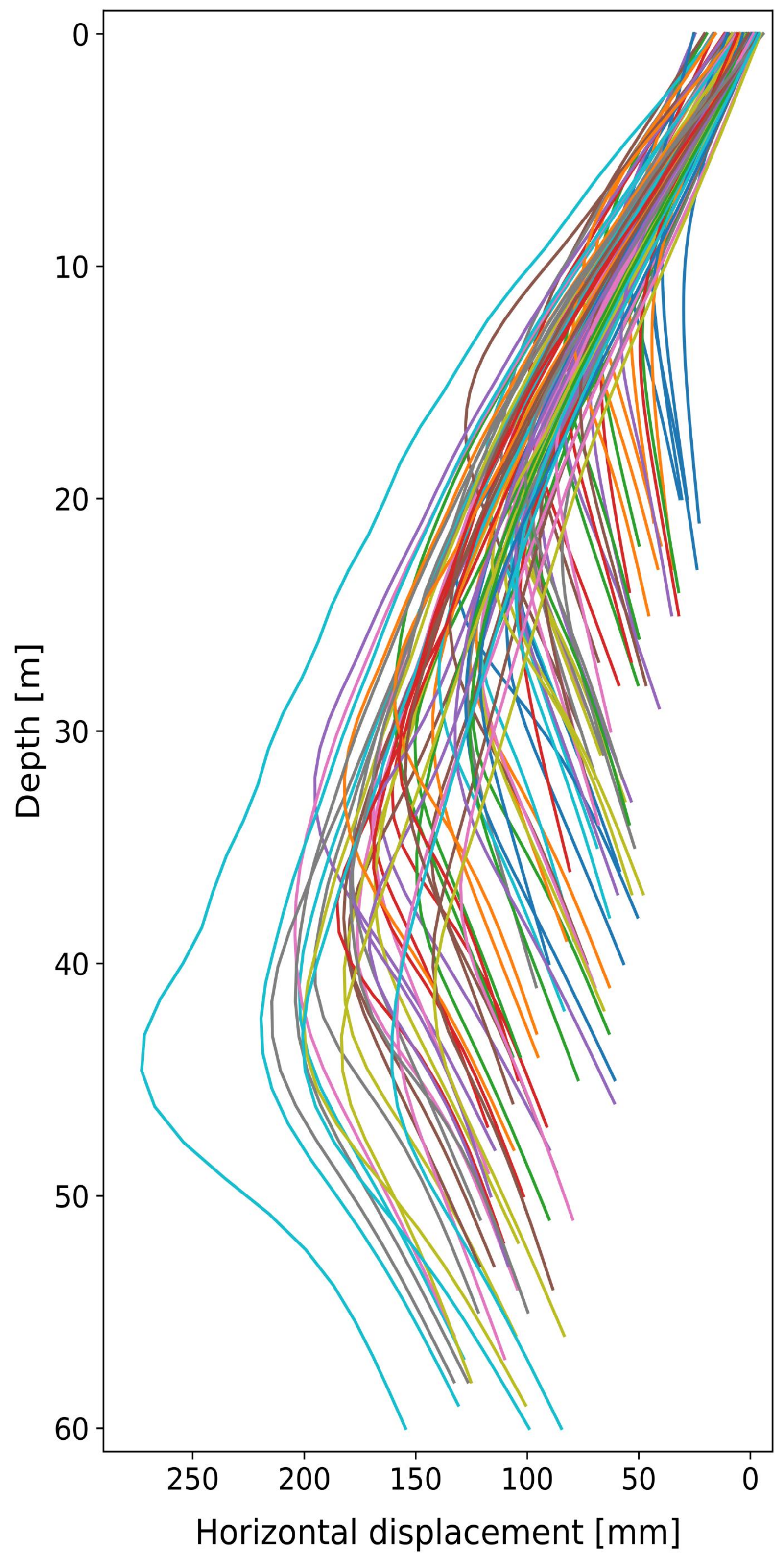


Figure 2: Virtualisation of the testing database

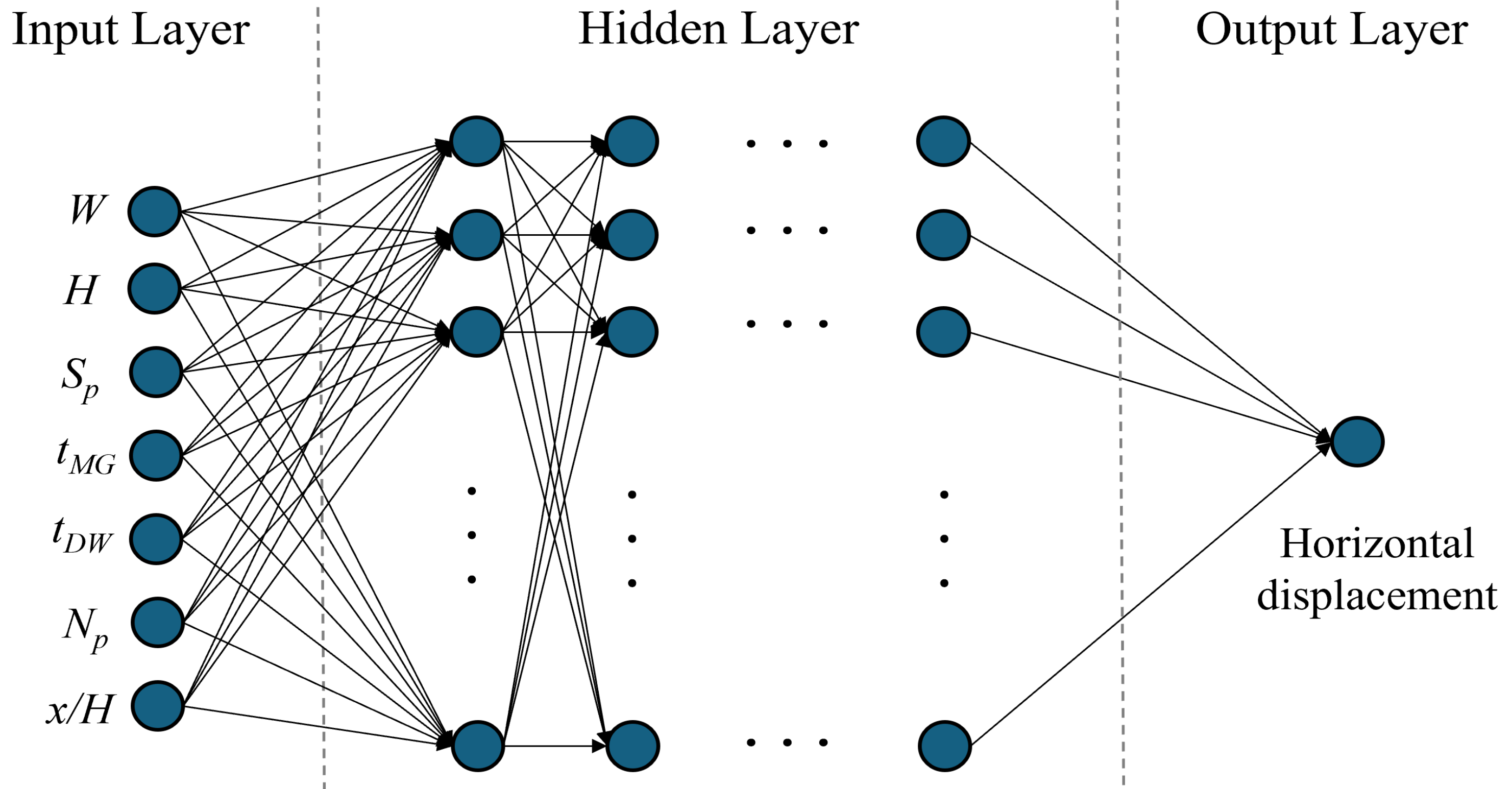


Figure 3: Architecture of the single-output ANN

Reference

Chollet, F., & others. (2015). Keras. https://keras.io

Forrester, A., Sobester, A., & Keane, A. (2008). Engineering design via surrogate modelling: a practical guide. John Wiley & Sons.

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