Congress on Numerical Methods in Engineering 2022
12-14 Septiembre 2022, Las Palmas de Gran Canaria, España

Characterization of pile stiffness using Artificial Neural Networks

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ABSTRACT

In order to determine the flexibility of pile foundations, appropiate models that include the soil-pile interaction mechanism should be considered. These types of models are usually complex and involve a high computational cost, making it difficult to transfer knowledge to other applications. In the literature, simplified expressions (e.g. [1, 2]) have been proposed to evaluate the stiffness of the piles in an efficient way, admitting some uncertainty in the result. The objective of this work is to build a surrogate model based on artificial neural networks (ANN) capable of predicting the stiffness of a pile foundation.

A dataset is generated to train the ANN. This synthetic data include the variables that define the foundation and the surrounding soil, and the foundation stiffness, which is evaluated through a previously developed continuous formulation [3]. Comparing the ANN predictions with the results obtained through the numerical tool, its potential to act as surrogate model is observed. The proposed ANN can be used to efficiently estimate the flexibility of pile foundation, without a significant loss of accuracy with respect to rigorous soil-pile interaction models.

This work has been performed within financial support from research project PID2020-120102RB-I00, funded by the Agencial Estatal de Investigación of Spain, MCIN/AEI/ 10.13039/501100011033.

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[2] George Gazetas. Seismic response of end-bearing single piles. *International Journal of Soil Dynamics and Earthquake Engineering*, 3(2):82–93, 1984.

[3] G.M. Álamo, A.E. Martínez-Castro, L.A. Padrón, J.J. Aznárez, R. Gallego, and O. Maeso. Efficient numerical model for the computation of impedance functions of inclined pile groups in layered soils. *Engineering Structures*, 126:379–390, 2016.

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September 13, 2022

Outline

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Motivation

Structural perspective

- Interest in introducing soil-structure interaction in a more rigorous way, instead of approximate methods
- Suitability of deep foundations for structures subject to higher loads and on less resistant soils

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Computational perspective

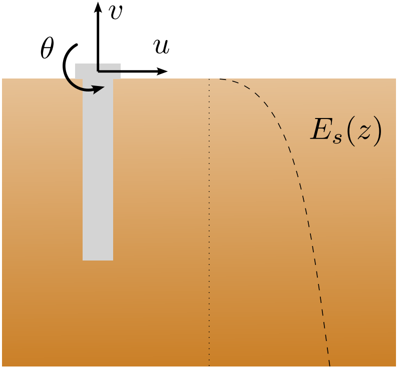
- Relative high computational cost procedure
- High development of Machine learning techniques in recent years

Aims and objectives

Develop a surrogate model based on ANN capable of estimating the stiffness of a pile in a soil with variable modulus of elasticity

Outline

Problem definition



$$\begin{Bmatrix} F_u \\ F_\theta \\ F_v \end{Bmatrix} = \begin{bmatrix} K_{HH} & K_{H\theta} & 0 \\ K_{H\theta} & K_{\theta\theta} & 0 \\ 0 & 0 & K_v \end{bmatrix} \begin{Bmatrix} u \\ \theta \\ v \end{Bmatrix}$$

Problem definition - Variables

Case definition

- Pile length: L
- Pile diameter: D
- Pile thickness: t
- Young's modulus of the pile: E_p
- Poisson's ratio of the pile: ν_p
- Reference Young's modulus of the soil: $E_{s,ref}$
- Relative top soil stiffness: γ_s
- Variation coefficient soil stiffness: n_s
- Poisson's ratio of the soile: ν_s

$$E_s(z) = E_{s,ref}\left(\gamma_s^{1/n_s} + \left(1 - \gamma_s^{1/n_s}\right)\frac{z}{L_p}\right)^{2n_s}$$

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Stiffness

- K_{HH}
- $K_{H\theta}$
- $K_{\theta\theta}$
- K_v

Problem definition - Dimensionless variables

Case definition

- $a_1 = \frac{L}{D}$ [0,100]
- $a_2 = 1 - \frac{2t}{D}$ [0,1]
- $a_3 = \frac{E_p}{E_{s,ref}} (1 - a_2^4)$ [10,50000]
- $a_4 = \nu_p$ [0.15,0.35]
- $a_5 = \nu_s$ [0.15,0.5]
- $a_6 = n_s$ [0,1]
- $a_7 = \gamma_s$ [0,1]

Stiffness

- $b_1 = \frac{K_{HH}}{E_{s,ref} D}$
- $b_2 = \frac{K_{H\theta}}{E_{s,ref} D^2}$
- $b_3 = \frac{K_{\theta\theta}}{E_{s,ref} D^3}$
- $b_4 = \frac{K_v}{E_{s,ref} D}$

Dataset generation

Input data generation

- Generation of uniform random data between limits of dimensionless variables
- Transformation to the problem with dimension

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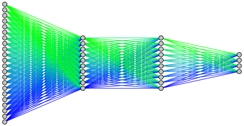
Output data generation - Structural model

- SSI is obtained from a continuum model, based in the integral formulation of pile-soil interaction with Green's functions of the layered halfspace
- Transformation to the dimensionless variables

Surrogate model generation



Surrogate model

- Define number of hidden layers
- Define number of neurons per hidden layers
- Train model using the train dataset
- MSE loss function: Loss $= \frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y_i})^2$
- Ensemble model: combining independent ANNs

Outline

Dataset information

Size

- Train dataset: 200.000 cases
- Test dataset: 150.000 cases

Architectures checked

Randomly generate between:

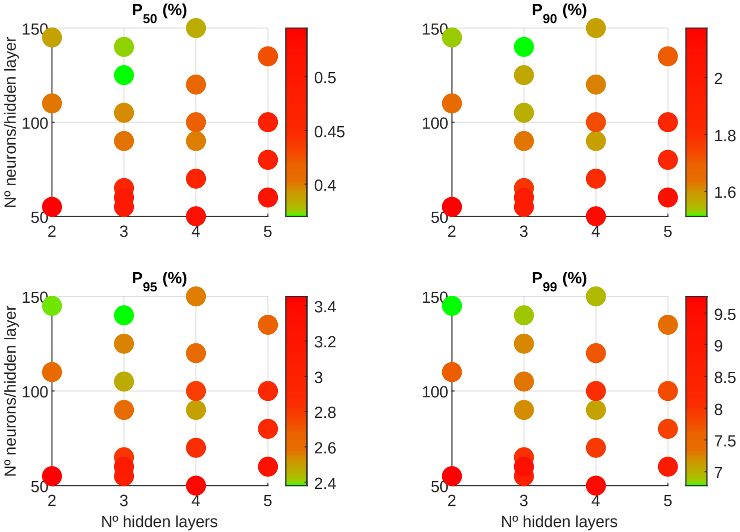
- Number of hidden layers: 2-5
- Number of neuron per hidden layer: 50-150

Performance evaluation

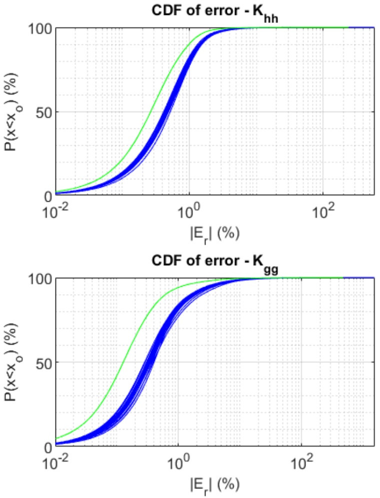
Percentiles of relative error in absolute value $|E_r|$:

$$|E_r| = \left| \frac{\widehat{K_{ii}} - K_{ii}}{K_{ii}} \right|$$

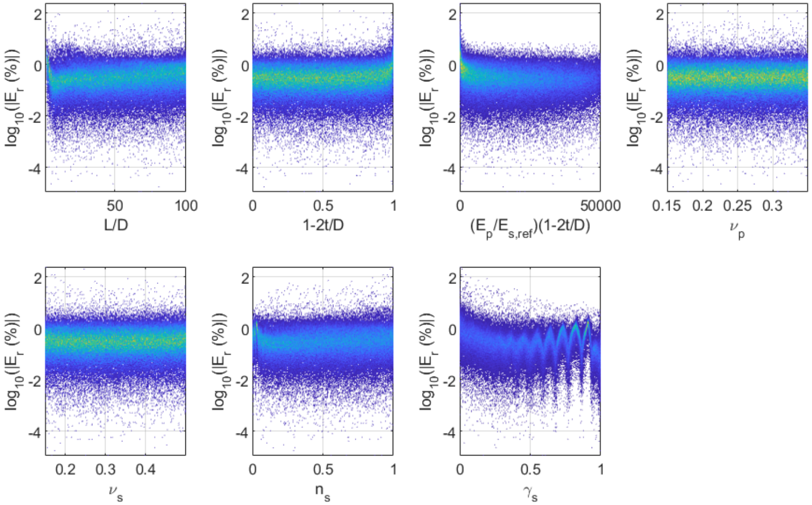
Architecture selection



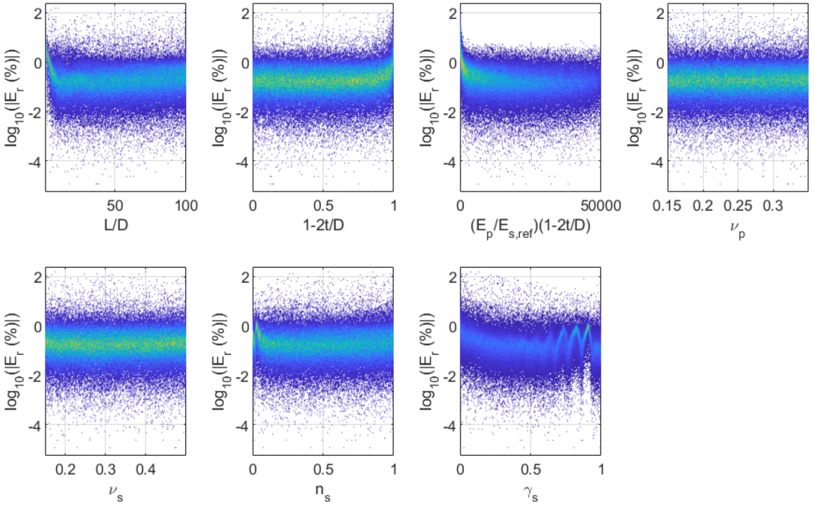
Ensemble model performance



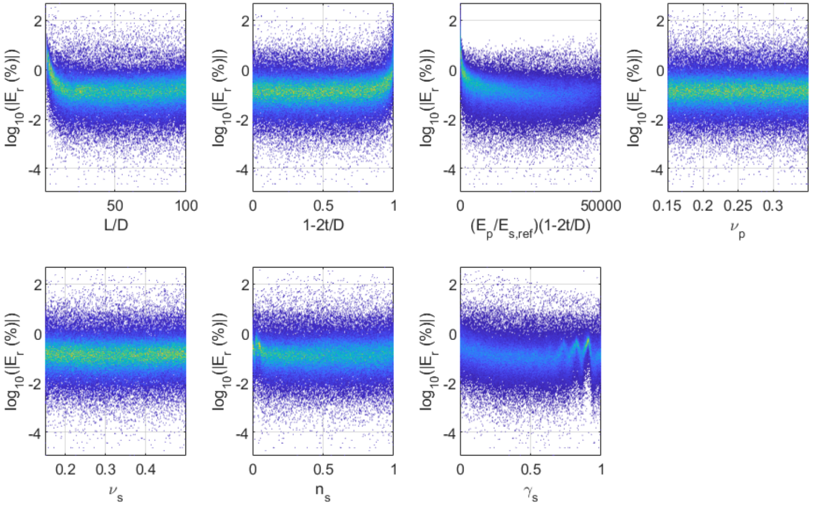
Error distribution - K_{HH}



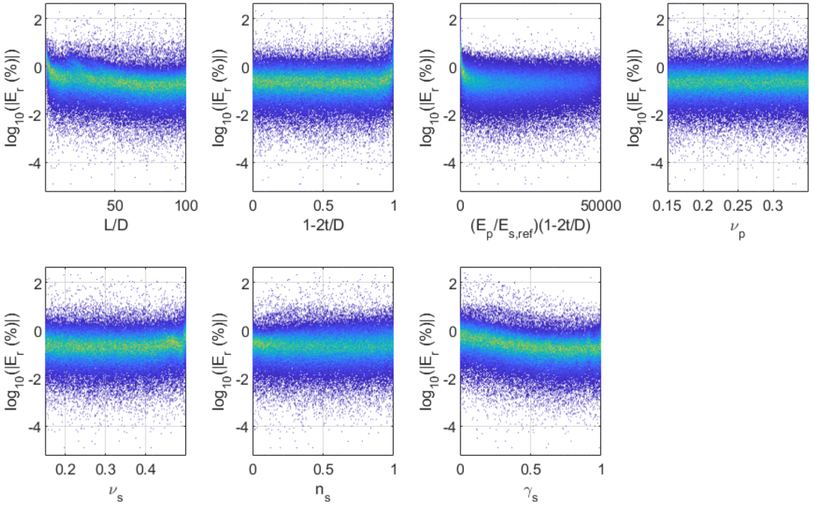
Error distribution - $K_{H\theta}$



Error distribution - $K_{\theta\theta}$



Error distribution - K_v



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Conclusions

Architecture

- A minimum statistical study is required before defining the surrogate model

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Surrogate model evaluation

- With the ensemble model, 99% of predictions have errors less than 6%
- The error is not homogeneously distributed over the search space, it increases where the value of the variable decreases

Acknowledgements

- Grant PID2020-120102RB-I00 funded by:

MINISTERIO DE CIENCIA E INNOVACIÓN

AGENCIA ESTATAL DE INVESTIGACIÓN

- Grant FPU19/04170 funded by:

MINISTERIO DE UNIVERSIDADES