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PREDICTION OF UNSUPPORTED EXCAVATIONS BEHAVIOUR WITH MACHINE LEARNING TECHNIQUES

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1 INTRODUCTION

Artificial intelligence and machine learning algorithms have known an increasing interest from the research community, triggering new applications and services in many domains. In geotechnical engineering, for instance, neural networks have been used to benefit from information gained at a given site in order to extract relevant constitutive soil information from field measurements [1]. The goal of this work is to use machine (supervised) learning techniques in order to predict the behaviour of a sheet pile wall excavation, minimizing a loss function that maps the input (excavation's depth, soil's characteristics, wall's stiffness) to a predicted output (wall's deflection, soil's settlement, wall's bending moment).

Neural networks are used to do this supervised learning. A neural network is composed of neurons which apply a mathematical function on their input (see Figure 1, left) and synapses which take the output of one neuron to the input of another one. For our purpose, neural networks can be understood as a set of nonlinear functions which can be fitted to data by changing their parameters. In this work, a simple class of neural networks, called Multi-Layer Perceptron (MLP) are used. They are composed of an input layer of neurons, an output layer, and one or several middle layers (hidden layers) (see Figure 1, right). A neural network learns by adjusting the weights and biases in order to minimize a certain loss function (for instance: the mean squared error) between the desired and the predicted output. Stochastic gradient descent or one of its variations are used to adjust the parameters and the gradients are obtained through backpropagation (an efficient application of the chain rule).

The interest in neural networks comes from the fact that they are universal function estimators, in the sense that they can approximate any continuous function to any precision given enough neurons. However, this can lead to over-fitting problems where the network learns the noise in the data, or worse, where they memorize by rote each sample [2].

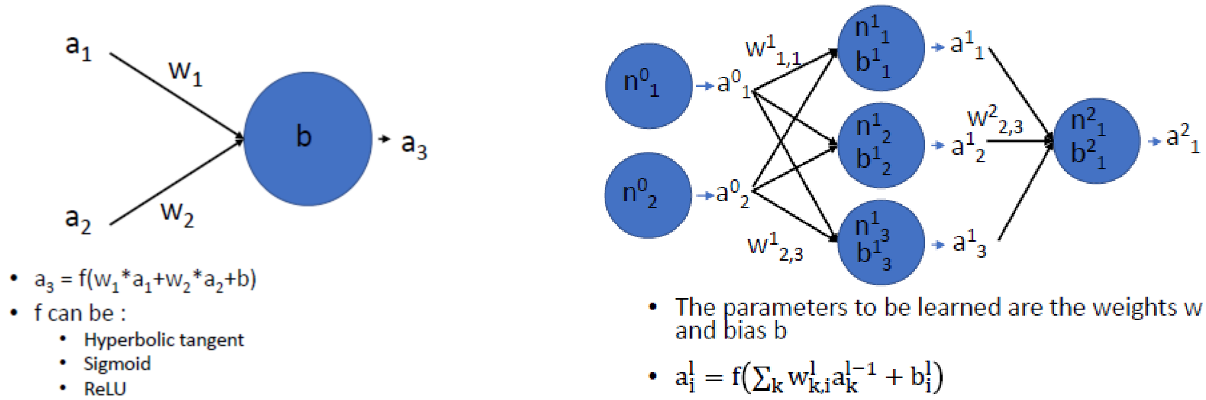


Figure 1: (left) Graph of a neuron with activation (a), bias (b) and weight (w) - (right) MLP graph

2 CREATION OF THE DATASET

For a neural network to learn, a dataset of excavations must first be compiled. The size of the dataset should be in hundreds or thousands of samples, and we do not have at hand such a large number of real excavation results. Thus, the dataset is obtained through numerical simulation using ZSWalls [3], a simple 2D deep excavation retaining wall analysis software based on the finite element method (FEM) program ZSOIL.

ZSOIL has been successfully used throughout the last three decades predicting the behaviour of large excavations in urban environments [4, 5].

In this first attempt to prove the feasibility of the method, the following simplifications have been taken into account: the support system is a free standing sheet pile wall (no anchors or struts), we only consider one soil, without water (unit weight = 20 kN/m^3, Poisson ratio and dilatancy angle are fixed), and the excavation width is proportional to its depth. The remaining meaningful variables (and their ranges, in brackets) are (see Figure 2 left):

- soil's parameters: loading E_{50} modulus [10 MPa; 100 MPa], friction angle phi [28°; 45°] and cohesion c [0 kPa; 10 kPa]. We use here the Hardening soil constitutive model with small strain extension [6], and assume E_{ur} = 4 x E_{50} and E_0 = 10 x E_{50}
- excavation's depth H [2 m; 8 m]
- wall's length L [1.1; 3.0] x excavation's depth
- sheet pile's characteristics (defining its moment of inertia I): 20 samples from the Arcelor Mittal catalogue [7]. We assume E_{steel} = 2 x 10^8 kN/m^2

From the background ZSOIL computation (Figure 2 right), the results extracted are: the wall's stability (with the hypothesis that a computation that does not converge means that the support system does not hold) and if convergence is obtained, the maximum settlement behind the wall, the maximum horizontal wall's displacement (or deflection) and the maximum bending moment in the sheet pile wall (Figure 3).

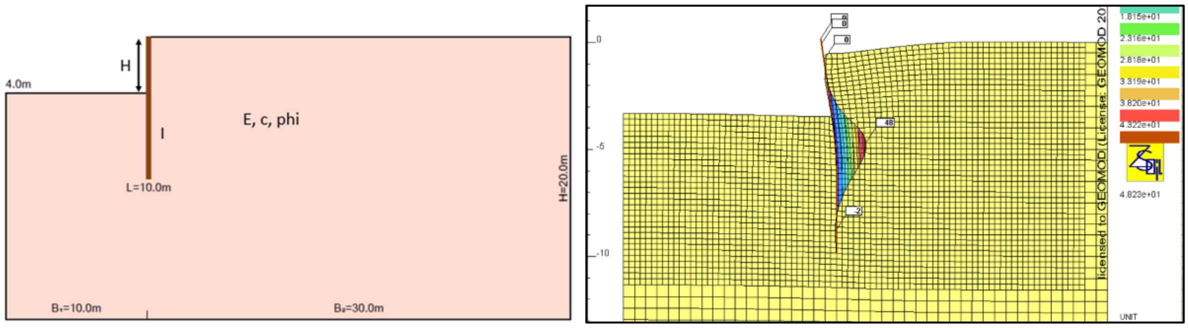


Figure 2: (left) ZSWalls input: definition of the excavation properties – (right) results of ZSOIL background calculation: bending moment and deformed mesh (x50)

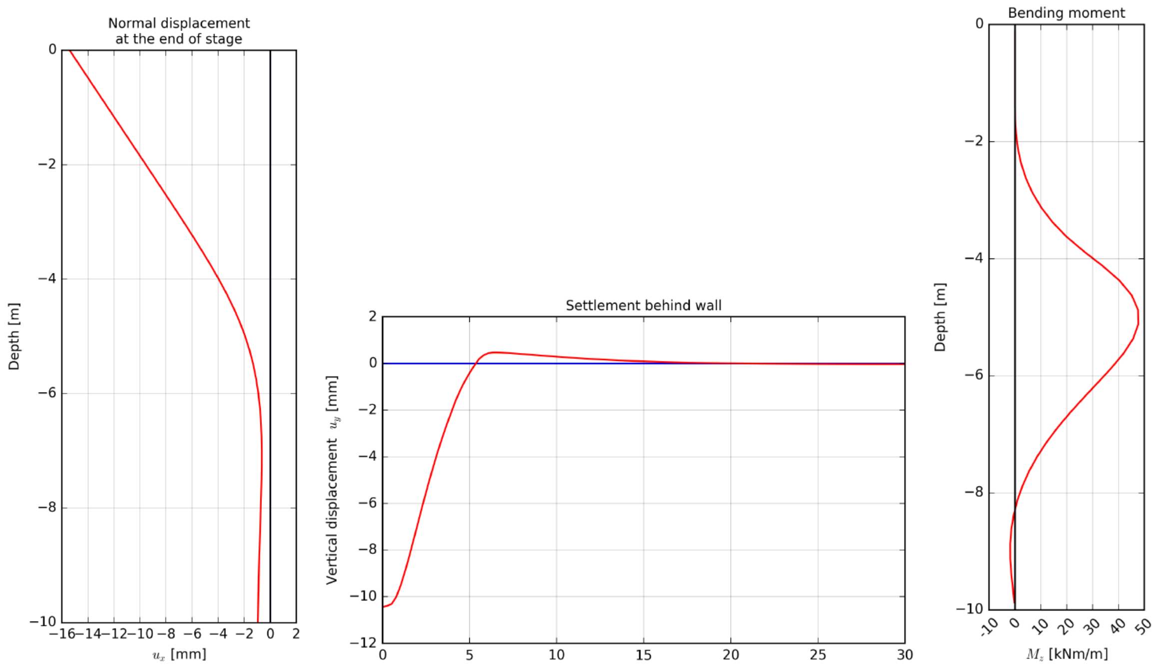


Figure 3: ZSWalls output: wall's deflection, soil's vertical settlement, wall's bending moment

3 ARCHITECTURE OF THE NEURAL NETWORK

The logical choice for the input of the neural network is the set of meaningful variables that defines the sample (soil's parameters, excavation's depth, wall's length and sheet pile's characteristics). Every other variable is either dependent on these ones - and this dependence is left to the neural network to learn, or should not influence the results. As for the output, it is simply the convergence status (yes/no), and three continuous outputs: the maximum settlement, the maximum horizontal wall displacement and the maximum bending moment in the sheet pile wall. Since the continuous outputs don't make sense if there is no convergence, the task should be separated in two: first a classification where the neural network predicts the convergence status, and then, if the convergence status is good, a regression can be done on the continuous variables.

All input values are scaled in order to have an expected value of 0 and a variance of 1. This, associated with the Glorot normal initialization of the weights, helped the network to learn faster. As for the output values, the convergence status is simply represented by a binary variable 0 or 1, and the continuous variables are linearly scaled between 0 and 1. This is necessary since a sigmoid activation function is used.

As mentioned before, a MLP neural network is built. The number of input and output neurons are defined by the number of inputs and output features. Thus, only the number of hidden layers and the number of neurons in each layer have to be decided. When the number of layers and neurons is augmented, the representational power of the network is also higher, but this comes with an increased number of parameters and a bigger risk of over-fitting.

The Tensorflow library for Python as well as the Keras API were used for all the experiments reported here.

4 RESULTS

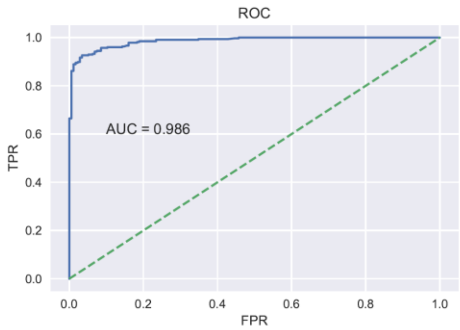
4.1 Classification

The complete dataset contains 5000 random samples, of which 37% did not converge.

The first task to accomplish is to predict whether the excavation is stable, i.e. evaluate the convergence of the FEM model. The architecture used is a simple MLP with one hidden layer of 10 neurons and a sigmoid activation function. No regularization technique is used. The output of the network is a real number between 0 and 1. An output close to 0 means a non-convergence prediction, and the opposite if the output is close 1. While there is a class unbalance, it did not create difficulties in the learning convergence. However, it reduces the meaning of accuracy (percentage of correct predictions) as 63% could be achieved with a network that only predicts convergence.

A preferred measure of the quality of prediction is the Positive Predicted Value (PPV) and the Negative Predicted Value (NPV) which corresponds to the ratio between correct predicted positive (resp. negative) over total predicted positive (resp. negative). Since, in civil engineering, false positives should be most avoided, it is possible to set the cut-off point higher to reduce them, at the cost of an overall decrease of accuracy.

The Receiver Operator Curve (ROC, see Figure 4, left) plots the False Positive Rate (FPR: fraction of negatives classified incorrectly) against the True Positive Rate (TPR: fraction of positives classified correctly). It is useful to show the tradeoff between correctly classifying positives and negatives cases when changing the cut-off point (see Figure 4, right). The Area Under the Curve (AUC) should be the closest possible to 1. It can be interpreted as the probability of correctly classifying a random positive case higher than a random negative case.



Cut-off	PPV	NPV
-	%	%
0.5	94.5	90.3
0.9	98.7	77.7
0.95	99.2	72.4
0.99	100	64.2

Figure 4: Receiver Operator Curve (ROC) and effect of cut-off point on PPV and NPV

4.3 Regression

The regression models were trained on the converged subset of the dataset (3141 samples), with 20% reserved for testing. Several models of increasing complexity were trained and evaluated: "10", with one hidden layer of 10 neurons, "30", with one hidden layer of 30 neurons, and finally "30red" or "30-20-10", with three hidden layers of neurons, containing respectively 30, 20 and 10 neurons.

As stated before, a more complex system has more representational power, as it can learn more complex functions. However, it becomes prone to over-fitting and care should be taken when training and evaluating the network. In this work, to avoid over-fitting, training was stopped when validation performance started to degrade.

As can be seen in Table 2, the performance of the model increases with its complexity: results are given for the different models with the coefficient of determination (R2), mean absolute error (MAE), mean relative error (MRE), 95 percentile of the relative error (RE95), mean relative error truncated (MRE_tr) and 95 percentile of the relative error truncated (RE95_tr). Note that truncation has been applied when absolute errors are below 2 mm (maximal settlement or wall's displacement) or 5 kNm/m' (maximal bending moment).

Table 2: Prediction results for the different models in terms of errors

	Model	R^2	MAE [m]	MRE	RE95	MRE_tr	RE95_tr
Settlement	10	0.983	1.7E-03	1.52	8.21	0.08	0.21
	30	0.988	1.3E-03	1.07	5.90	0.06	0.15
	30-20-10	0.989	1.4E-03	1.40	7.00	0.05	0.12
Wall deviation	**Model**	**R^2**	**MAE [m]**	**MRE**	**RE95**	**MRE_tr**	**RE95_tr**
	10	0.982	1.3E-03	0.22	0.88	0.04	0.17
	30	0.991	1.1E-03	0.16	0.54	0.02	0.14
	30-20-10	0.991	9.8E-04	0.12	0.37	0.02	0.11
Moment	**Model**	**R^2**	**MAE [kN]**	**MRE**	**RE95**	**MRE_tr**	**RE95_tr**
	10	0.995	2.7	0.13	0.34	0.02	0.10
	30	0.995	2.6	0.13	0.30	0.01	0.08
	30-20-10	0.994	2.7	0.12	0.30	0.01	0.08

Figure 5 shows the behaviour of the three different models: the predicted values for settlement, deflection and bending moment given by the neural network are compared to the "correct" computed values.

It can be noticed that there is a tendency to predict lower values. This probably comes from the choice of the relative error as a criterion for model selection: smaller predictions are bounded by 100% whereas bigger predictions are unbounded.

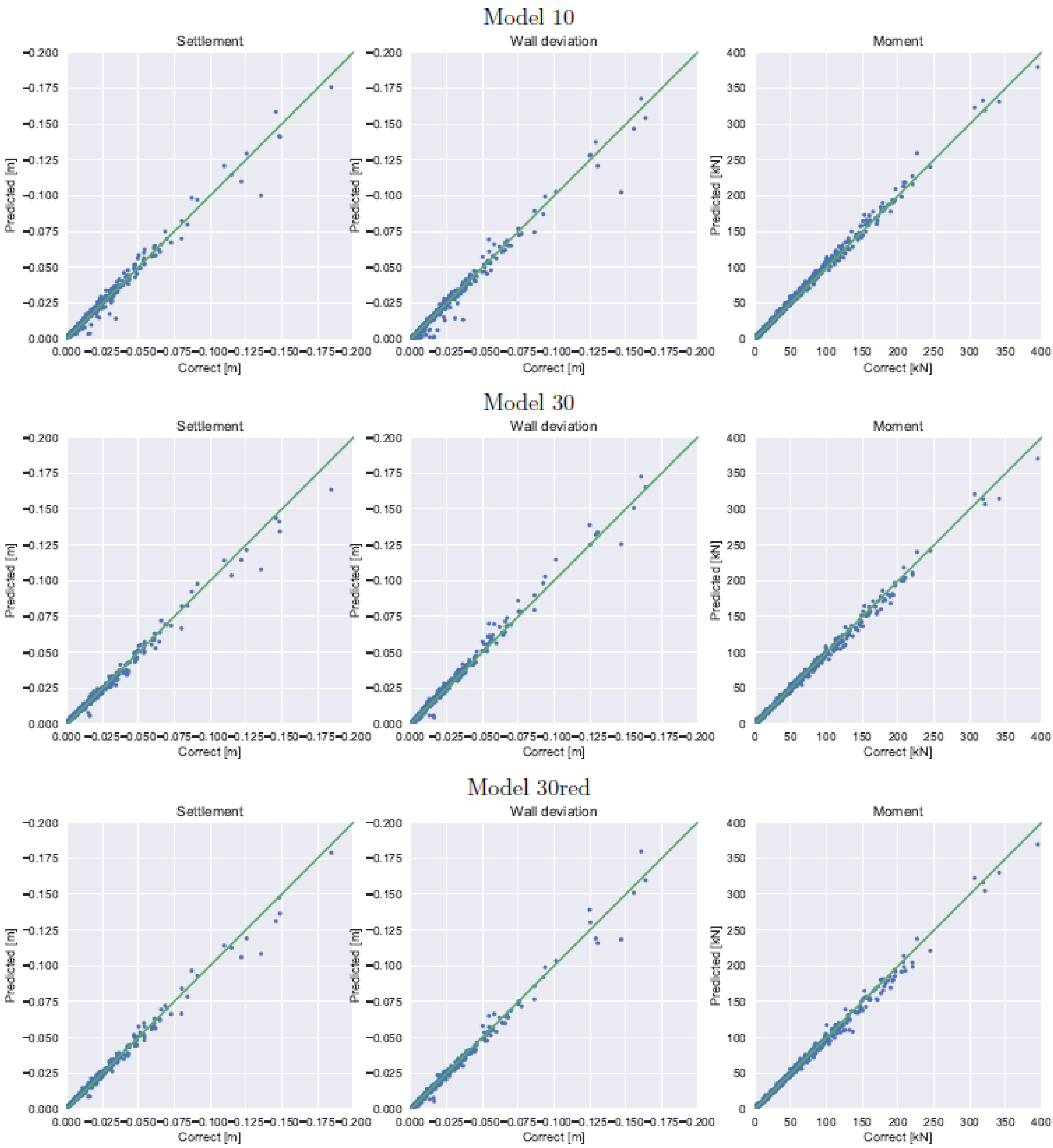


Figure 5: Predicted against computed soil's settlement, wall's horizontal displacement and bending moment

5 CONCLUSIONS

The resulting model can predict accurately if an unsupported excavation is stable. Soil's settlement, wall deflection and maximum bending moment in the sheet pile wall can also be predicted with small relative errors (less than 5%).

In future work, we would like to generalize this approach to real-life cases, building a tool capable of predicting the behaviour of an excavation support (slurry or sheet pile wall, with anchors or struts) for a given set of data (stratigraphy, groundwater table, excavation's depth), without calculating it with conventional engineering software (finite element method), but rather using an existing dataset.

Once this tool will be functional, it could also be used in order to find an optimal excavation design in terms of costs or planning, under constraints (maximal acceptable horizontal displacement for instance).

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