A SPECIALIST PROGRAM TO EVALUATE SLOPE STABILITY

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Abstract. *Slope stability is one of the processes evaluated during the construction of dams, embankments and tailings. Aiming the optimization of this evaluation, this study applies theories and methodologies that provide the slope stability safety factor (SF) efficiently. The study is concentrated on the development of a specialist program that evaluates the slope SF with minimum resources and time. An Artificial Neural Network (ANN) is trained using the results of a number of numerical simulations carried out with a nonlinear finite element (FE) program. In order to obtain the SF through this numerical approach, the Strength Reduction Method is used together with the FE program Abaqus and a subroutine, written in Python language, which permits the parametrization of the problem variables. Finally, the MATLAB program is used to construct and train the ANN using the soil strength parameters as input data. A single layer slope stability problem is applied to illustrate the methodology presented. A set of tests varying the number of samples and the architecture of the network is investigated. According to the results, good performance is reached.*

Keywords: *Slope Stability, Finite Element Method, Safety Factor, Artificial Neural Network*

1 INTRODUCTION

Slope stability is one of the processes evaluated to verify safety in natural hillsides and to construct dams, embankments and tailings (industrial, mining or urban). In the case of natural slopes, if the safety criterion is not reached, some security measures can be taken (Song, 2012). In the construction of artificial slopes, scenarios are developed with different soil properties and slope geometry. For each case, the safety factor (SF) is calculated in order to define the best project.

The SF shows how far the slope is in relation to the worst failure scenario. The SF is based on soil properties, slope geometry and overloads. This factor can be evaluated in several ways. Considering analytical approaches, the most widely used is the limit equilibrium method. It includes the Simplified Bishop method, Spencer's method, and Janbu's Simplified method, which are discussed, for instance, in Cheng et al. (2007) and Fredlund et al. (1981). Duncan et al. (1996) and Zheng et al. (2005) highlight some restrictions of the analytical approach when more complicated slopes are considered. As an alternative, the finite element method (FEM) is adopted in the literature (Matsui et al., 1992 and Yang et al., 2012).

In addition, slope stability analysis contains intrinsic uncertainties related to soil properties. These uncertainties can be evaluated through a probabilistic analysis. For that, the acquisition of a limit state function can make the analysis easier. Once the FEM cannot express an SF function in an explicit form, some computational intelligence techniques can be adopted to obtain an approximation of the SF function.

The Artificial Neural Network (ANN) is a computational method that has been used in recent studies to solve engineering problems. Damage detection in structures (Aydin et al., 2014) and streamflow forecasting (Talaee, 2014) are studies using ANN successfully. A study using the ANN for slope reliability analysis is presented by Cho (2009).

In this paper, a response surface of the SF is constructed using an ANN. The input samples used to train the network are the cohesion and the friction angle, and the output is the SF obtained through the SRM using the commercial software ABAQUS.

2 SLOPE STABILITY

In order to obtain the safety factor (SF) for numerical analyses, the Strength Reduction Method (SRM) is used. In Cheng et al. (2007), three main advantages of the SRM are summarized. The first positive aspect is that the failure surface is defined by the shear strain resulting from the gravity loads and the strength parameters, i.e. requiring no slip shape assumption. Secondly, no interslice shear force is considered. At last, in addition to the SF, the method can provide stresses, displacements, pore pressures and other results.

The resistance parameters of the SRM: cohesion – c and friction angle – ϕ, are adjusted constantly until the slope reaches instability. Equations (1) and (2) show how this adjustment is made.

$$c_{it} = \frac{c}{SF_{it}} \quad (1)$$

$$\phi_{it} = \arctan\left(\frac{\phi}{SF_{it}}\right) \tag{2}$$

In the previous equations, c and ϕ are the actual parameters of the model, while c_{it} and ϕ_{it} are the values for the next iteration. They depend on the safety factor of each trial, SF_{it}. Figure 1 illustrates how the SF is determined. It occurs when a controlled point of the model has a large horizontal displacement increment.

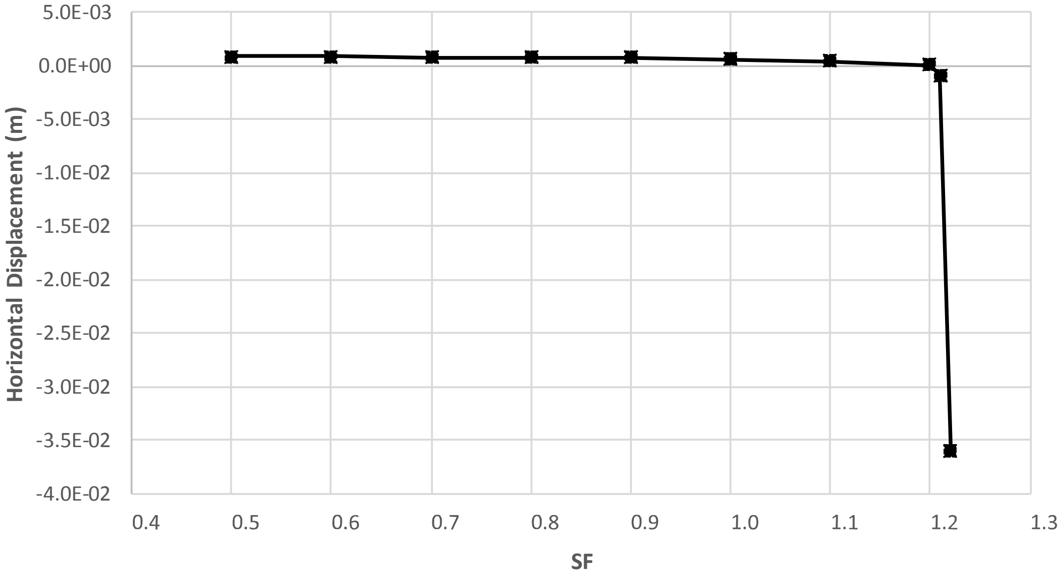

Figure 1. Illustration of the Strength Reduction Method

2.1 Artificial Neural Network

The ANN is an artificial intelligence scheme based on the human nervous system. The network learns some behavior from experience and it can predict unknown cases of the problem. This experience is obtained through samples that are constituted by input and output variables (neurons). For a successful operation, the network must be correctly trained. This training is executed adjusting the weights (connections) of each parameter in the network function. These weights are randomly generated at the beginning of the analysis. Thus, they are updated iteratively, aiming to reduce the mean-squared error (MSE) between the output predicted by the ANN and the output target. In this paper, the Levenberg-Marquardt Backpropagation algorithm (Eberhart et al., 1990) with hidden layers is used to train the network, and the Multilayer Perceptron Feedforward architecture (Hornik et al., 1989), (Kang et al., 2017) is adopted. Figure 2 shows a simple network structure where, x_n is the input layer, w_n is the respective weight, n is the number of variables, θ is the bias, u is the action potential, $g()$ is the activation function, and y is the output layer.

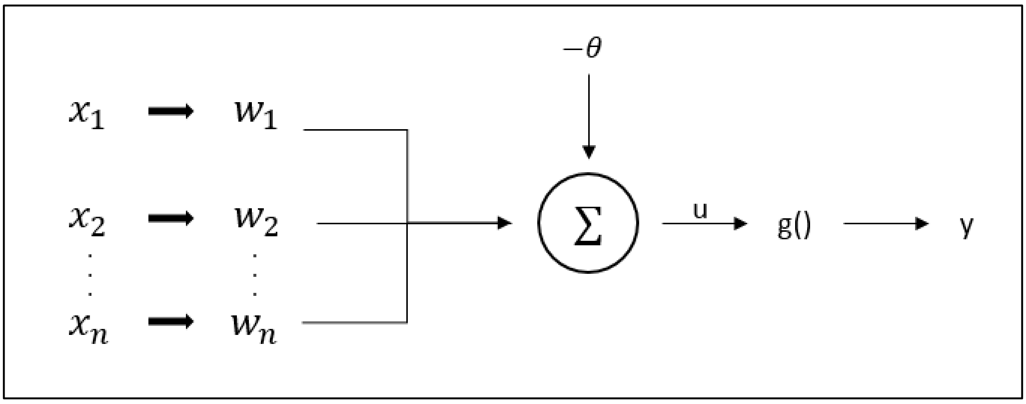

Figure 2. Structure of a simple ANN

The number of neurons in the hidden layer is established by a trial-and-error process. This measure determines the network accuracy (Heaton, 2005), (Eberhart et al., 1990). In this paper, the hyperbolic tangent sigmoid function (Figure 3) is used to transfer the input layer neurons to the hidden layer neurons and those to the output layer neurons. In addition, the samples used in the network are divided into three groups. The first one is the training group, which is used to adjust the weights and the bias. The second group includes the validation samples. Their errors are monitored during the training and when they reach a minimum, the weights are established The last one is the test group, which is not used in the training. However, this group is used to compare different models. If its error is minimum at a significantly different iteration step from the validation group, this might indicate a bad arrangement of the data set (Pereira et al., 2014). In this paper, the 0.70, 0.15 and 0.15 values are adopted for each group respectively.

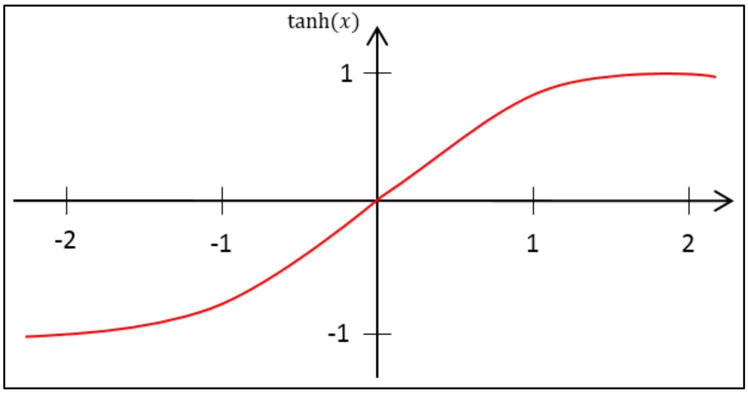

Figure 3. Hyperbolic tangent sigmoid function

Finally, a treatment that must be considered before training the ANN is the input data normalization. This process consists of scaling the input parameters to an equal range. If this procedure is not performed, the neural network operation can vary the results extremely. Furthermore, the ANN training time can increase.

3 METHODOLOGY

For the purpose of integrating the Artificial Neural Network (ANN), the Finite Element (FE) model and the Strength Reduction Method (SRM), an automatic workflow was developed.

The network training was performed using the software MATLAB, while the commercial FE software ABAQUS was adopted as the numerical simulator. An ABAQUS script was written in Python programming language to facilitate the development of new models. The specific output required for the ANN has been customized using Python and Lua codes.

Figure 5 shows the workflow composed by the following steps:

- MATLAB generates the input samples randomly.
- A geomechanical model file (parametrized script for ABAQUS) is provided.
- For each dataset, a new geomechanical file with new strength parameters is generated.
- From this modified input file, the SRM is performed looking for the critical SF.
- Once the SFs are obtained for the whole sample, the ANN is trained.

4 EXAMPLE APPLICATION

4.1 Numerical model

A 2D finite element model is created to obtain the horizontal displacement of the slope (Figure 4). The common plane strain condition is adopted and the slope is modeled with 8-node biquadratic elements. In order to simulate a real slope, the boundary conditions reproduce an "infinite" model while the lateral nodes are blocked in the horizontal direction.

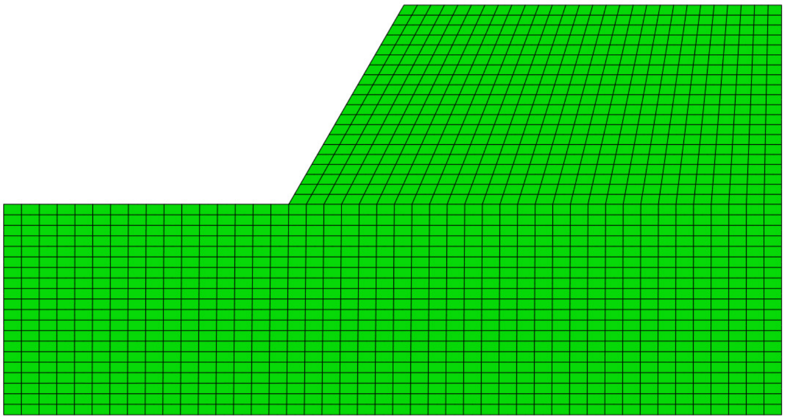

Figure 4. Mesh used in the model

The base nodes are restricted in the vertical direction and free to move sideways. The geostatic stress field was simulated prior to the mechanical analysis. Initially, the top nodes of the slope are also blocked, and the gravity load is applied to the whole region. Later, in the mechanical calculation, the top nodes of the model are released.

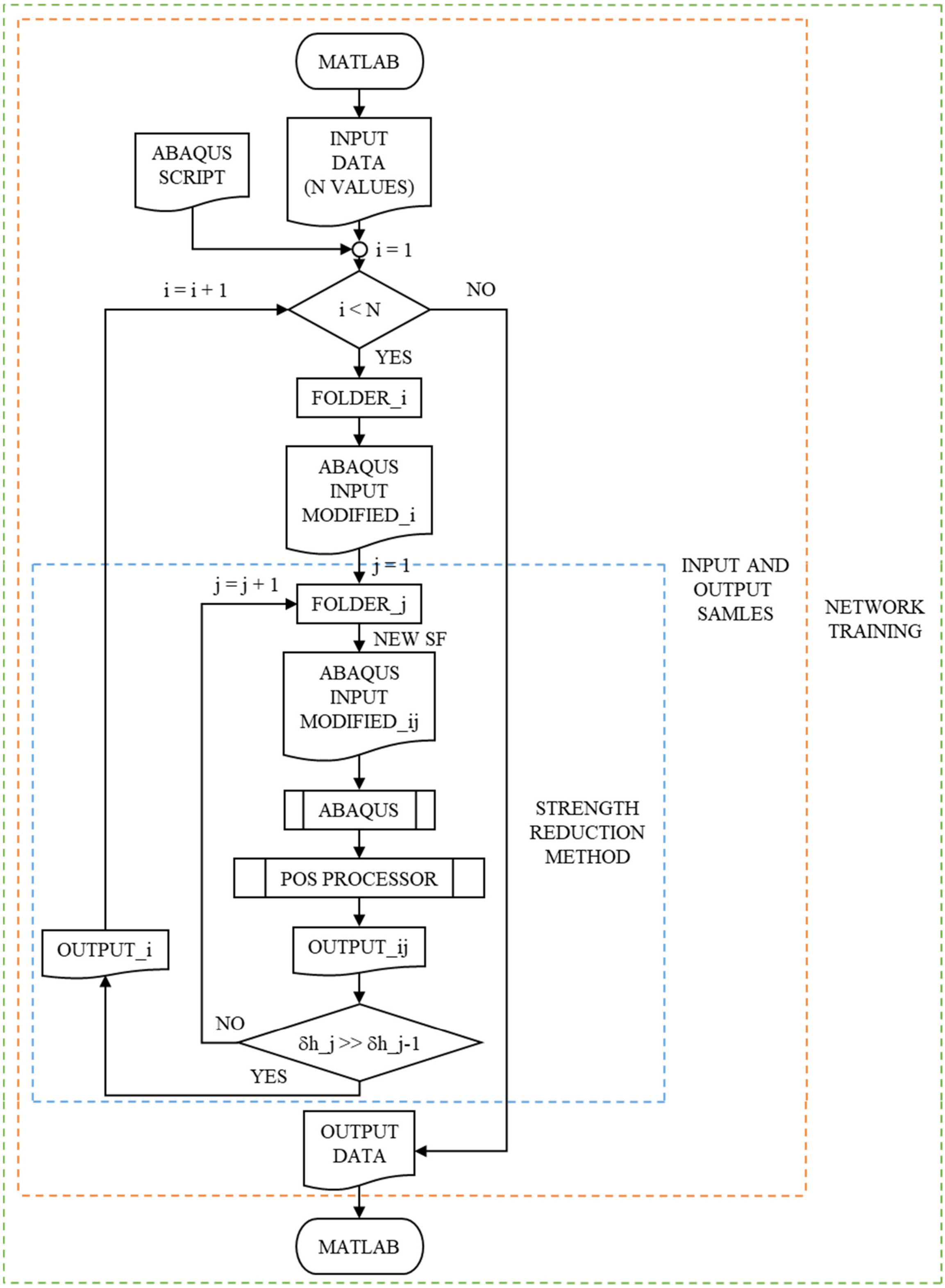

Figure 5. Workflow of the specialist program to evaluate slope stability

4.2 Example analysis

An example (Abaqus Documentation, 2012) is performed using the methodology described in Section 4. A one-layer slope is adopted for the application of the procedure described. The model geometry is shown in Figure 6 and Table 1 summarizes the soil properties.

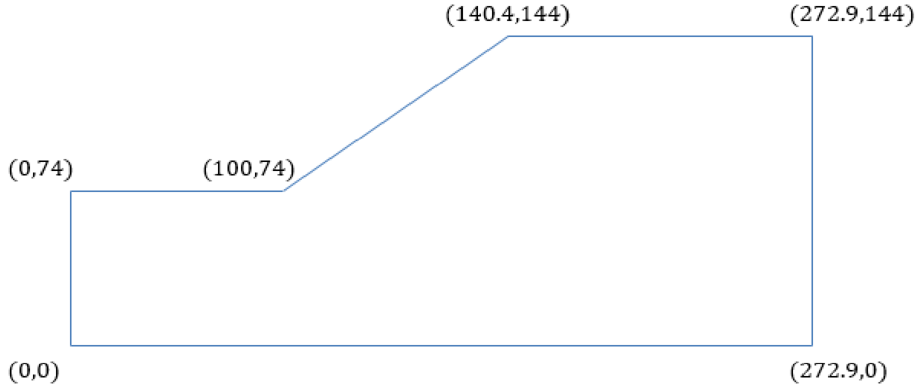

Figure 6. Model geometry

Table 1. Soil Properties

Soil Properties	
Cohesion	110 kPa
Friction angle	35º
Unit weight	25 kN/m³
Young modulus	28 GPa
Poisson coefficient	0.2

Slope stability is fundamentally governed by the Mohr-Coulomb criterion, which is estimated by the soil strength properties: cohesion and friction angle. In this study, they are the input variables of the ANN. The Latin Hypercube Sampling method is used to generate reasonably dense training samples, as recommended by Hurtado et al. (2001). The same range adopted in previous studies (Goh, 2005) is used in this paper, Eqs. (3) and (4),

$$x_{max} = \mu_x + (3 \times \sigma_x) \quad (3)$$

$$x_{min} = \mu_x - (3 \times \sigma_x) \quad (4)$$

where μ_x is the mean value of the variable, here taken as the cohesion and friction angle values of the model. The standard deviation is defined by Eq. (5).

$$\sigma_x = COV \times \mu_x \quad (5)$$

where COV is the coefficient of variation. Table 2 shows the values adopted for μ_x and COV.

Table 2. Values used to define the range of the ANN samples

	μ_x	COV
c	110 kPa	0.2
ϕ	35º	0.1

4.3 Results and discussion

In this paper, two trial-and-error processes are performed in order to obtain the best accuracy of the network. One is applied to establish the number of neurons in the hidden layer. The other is related with the number of training data sets. Table 3 presents the test results performed changing the number of samples and the ANN structure.

Table 3. Regression and MSE for different ANN structures and numbers of samples

Samples	ANN Structure	MSE	Regression
16	2-1-1	0.014314	0.95838
	2-2-1	0.00060988	0.98233
	2-3-1	0.0063365	0.9605
50	2-1-1	0.010419	0.97142
	2-2-1	0.0062219	0.98723
	2-3-1	0.0021905	0.98881
100	2-1-1	0.0082738	0.96886
	2-2-1	0.0025771	0.98838
	2-3-1	0.0015382	0.99586
250	2-1-1	0.011388	0.96990
	2-2-1	0.0061517	0.98737
	2-3-1	0.00096818	0.99722
500	2-1-1	0.011814	0.97149
	2-2-1	0.0047815	0.98674
	2-3-1	0.0012596	0.99714

The higher regression value and the lower mean-squared error (MSE) are the criteria used to determine the best network structure. The regression value, also known as correlation coefficient, estimates the relationship between the output from the network and the target.

The sequence of numbers in the ANN Structure column means: numbers of neurons in the input layer – number of neurons in the first hidden layer – number of neurons in the second hidden layer – numbers of neurons in the n hidden layer – number of neurons in the output layer. Where n is the number of hidden layers. Figure 7 shows an example

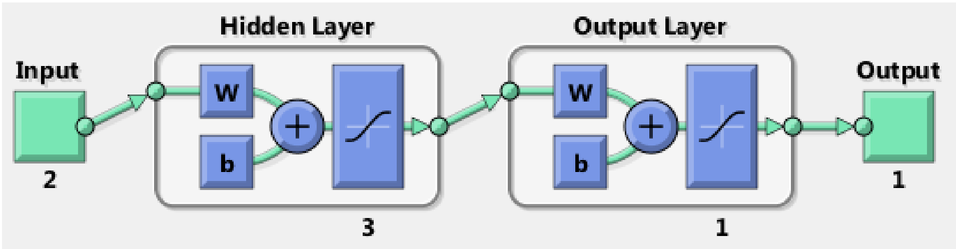

Figure 7. Configuration of a 2-3-1 ANN structure

In general, according to the results obtained from the tests, a small number of samples seem to be capable of training the ANN adequately. Based on the results, the ANN structures with one or two neurons in the hidden layer do not have a regression value higher than 0.99, independently of the number of samples. In order to obtain more accurate results, the architecture 2-3-1 with at least 100 samples reaches that value with an approximate error of 10E-3. Figure 8 shows the traning process of the ANN (with 500 samples and 2-3-1 architecture)

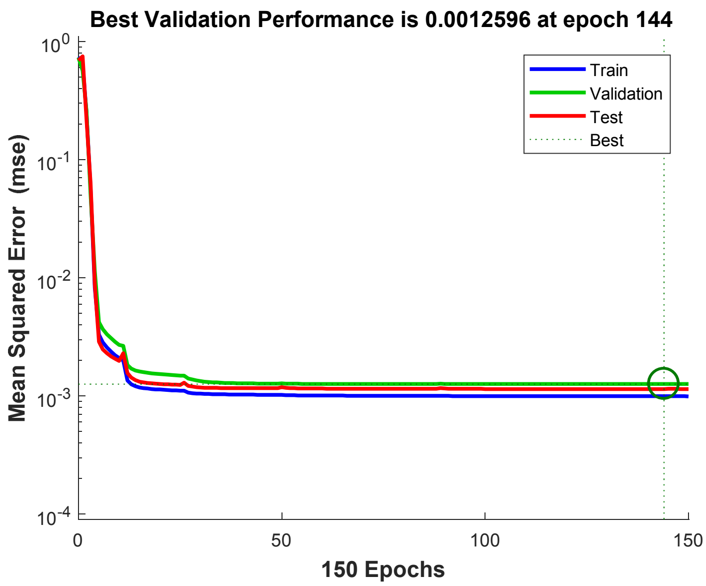

Figure 8. Performance: Mean-squared error (MSE) in training the ANN

Figure 9 shows a detailed representation of the Regression plot. It allows a fast comparison between the SF computed by the FEM and the SF calculated by the ANN. It can be seen that most of the data are very close to the line $Y = T$.

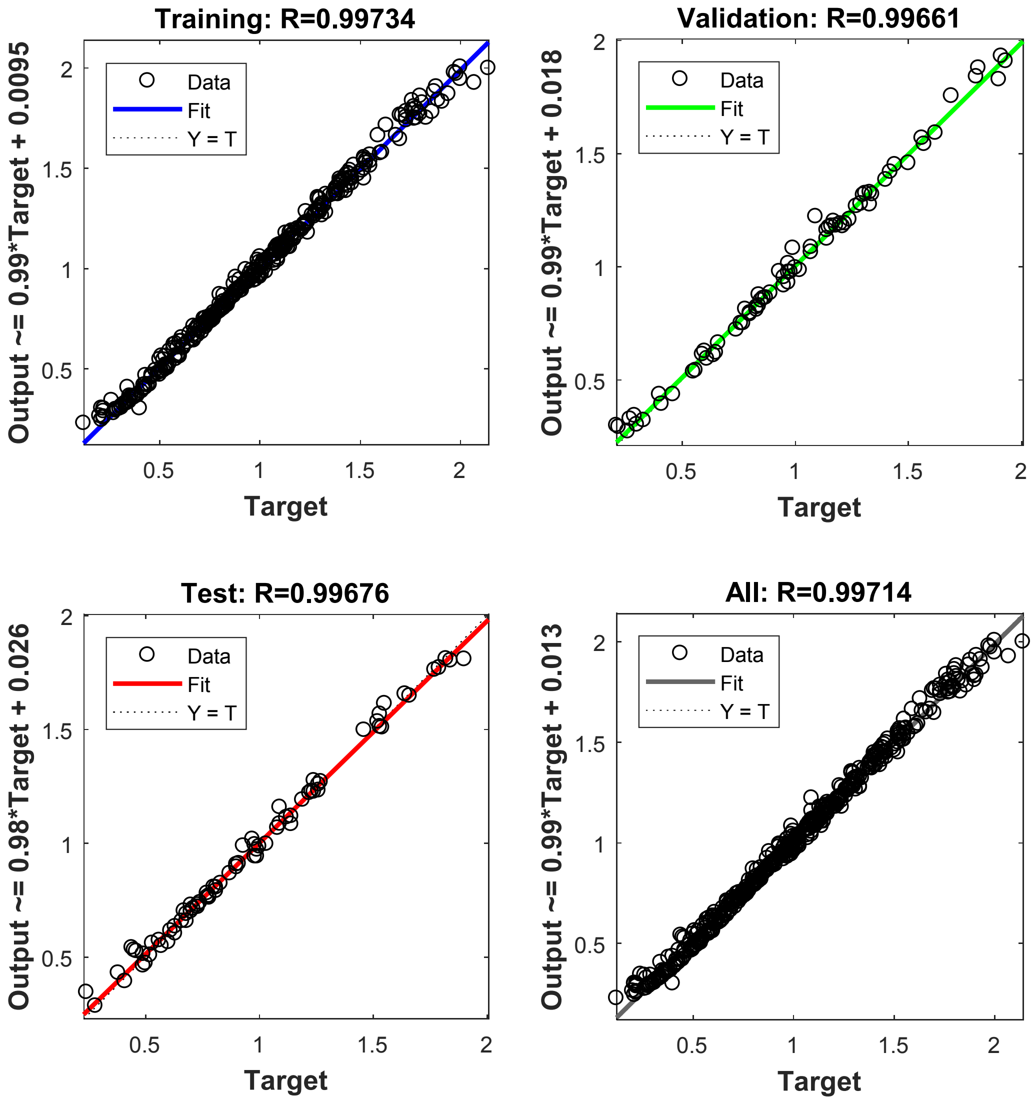

Figure 9. Comparison between the SF computed by the FEM and the SF calculated by the ANN: (Top-Left) results of the training; (Top-Right) validation of the fitting; (Bottom-Left) test results; and (Bottom-Right) the global fitting

5 CONCLUSION

The development of effective and efficient methods is highly desirable in engineering practice. In order to reach this objective, this paper is part of a study focused on the estimation of the critical safety factor (SF) of a slope through a specialist program.

Part of a geotechnical engineering project, especially in slopes, is to study the stability conditions. A measure to the stabilization of slopes is the safety factor. In this paper, a numerical approach is applied to analyze the slope conditions and, using the strength reduction method, the SF is obtained. Furthermore, an alternative approach is taken to optimize this evaluation. An Artificial Neural Network (ANN) is trained to provide the slope safety factor.

Based on the results, the performance of ANN can be considered very satisfactory for the problem of slope stability. Even a small number of samples and a simple architecture seem to be able to train the ANN adequately. However, a network with a structure with 2 neurons in the input layer, 3 neurons in the hidden layer and 1 neuron in the output layer, and with at least 100 samples reaches a better performance.

Although the methodology presented was developed together with a single layer slope stability analysis problem, this approach is general and can be extended to more sophisticated slope problems.

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