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BACK ANALYSIS OF SCL TUNNELS BASED ON ARTIFICIAL NEURAL NETWORK

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Abstract
Soil parameters obtained as a result of a site investigation are prone to a certain error. In case of numerical modelling it is reasonable to clarify these parameters to ensure that the behaviour of numerical model is as close to reality as possible. Currently, the-state-of-the-art method is to perform sensitivity analysis and back analysis of soil parameters. This paper presents simplified method to perform above analysis to clarify soil parameters and to ensure behaviour of numerical model as close as possible to reality on an example of two similar SCL tunnels. One of the so-called "soft computation" method has been used – Artificial Neural Network [1].

Streszczenie
Parametry gruntowe uzyskane w wyniku badań polowych i laboratoryjnych są narażone na pewny błąd. W przypadku modelowania numerycznego zasadne jest doprecyzowanie tychże parametrów w celu zapewnienia możliwe najbardziej zbliżonego do rzeczywistości zachowania modelu numerycznego. Aktualnie jedną z najnowocześniejszą metodą jest przeprowadzenie kolejno analizy wrażliwości oraz analizy wstecznej parametrów gruntowych. W artykule przedstawiono uproszczoną formę przeprowadzenia w/w analiz w celu doprecyzowania warunków gruntowych i możliwie jak najbardziej zbliżonego do rzeczywistości zachowania modelu numerycznego na przykładzie dwóch bliźniaczych tuneli SCL. Posłużono się jedną z metod inteligentnych obliczeń numerycznych zwanych sztucznymi sieciami neuronowymi [1].

Keywords: **Sprayed Concrete Lined tunnels; Back analysis; Sensitivity analysis; Artificial Neural Network.**

1. INTRODUCTION

The structure of interest is a part of the Fővám Square station of the 4th metro line in Budapest. The analysed structure consists of two similar tunnels made in Sprayed Concrete Lined (SCL) technology. Geotechnical conditions examined in site investigation turned out to be highly complex with many fault zones, over consolidated soil and high pore pressure [1], [2].

Geotechnical parameters obtained from site investigation roughly describe real conditions. In some cases behaviour of soil significantly differs from description after site investigation. Many factors have significant influence on the obtained results, such as size of samples taken to the laboratory. To specify geotechnical parameters different methods can be used. One of the most promising methods is the adjustment of the numerical model to the real conditions based on measured displacements obtained after excavation of a small area. This gives the possibility to check the design correctness and to respond right on time. This method is called a back analysis because numerical model is fitted in backward direction to behave like in reality. Back analysis is often applied in prediction of tunnel behaviour, real values of parameters of soil and other variables which are hard to obtain with use of traditional methods. In this paper Artificial Neural Network (ANN) was used to perform the sensitivity and back analyses. General rules of ANN are presented in chapter 2 and shown in figure 1 and 2. For the sensitivity analysis specific scheme of ANN is shown in figure 3 while the scheme of back analysis is presented in figure 8.

2. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network is a system which attempts to describe the behaviour of the neural system in a human brain. Neural system is composed of various types of neurons. A scheme of a simple biological neuron is shown in Figure 1 but in fact neurons are much more complicated.

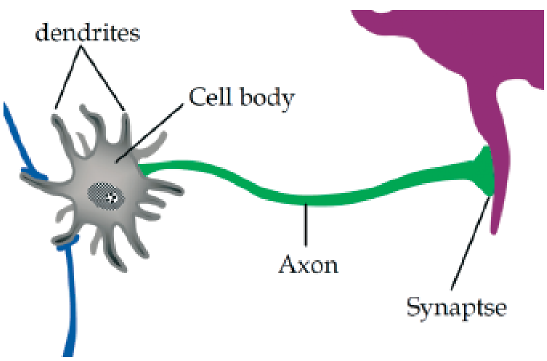

Figure 1.
Simplified scheme of biological neuron [3]

In general, Artificial Neural Network can be described by a scheme shown in Figure 2. Three main layers of neural network (input, hidden and output layers) can be identified. For user two layers are the most important: an input layer, which is responsible for input parameters, and an output layer. Parameters of interest are received from the output layer. At the beginning the output layer consists of target parameters which are used to train and verify the network. Finally, when the process is finished, the whole output layer is used to receive the values of the parameters of interest. The hidden layer may consist of several sub layers; the level of complexity depends on the relationship between the input and output parameters. Each layer is related by bonds with the specific weights. ANN may contain many summing junctions and the corresponding activation functions which form the so-called hidden layer. Sometimes, task complexity determines the use of multiple hidden layers with different activation functions. There are several questions that must be answered before starting to create ANN: the number of hidden layers, hidden neurons, training data etc. [4].

ANN may contain many summing junctions and the corresponding activation functions which form the so-called hidden layer. Sometimes, task complexity determines the use of multiple hidden layers with different activation functions. However, unreasonable increase of the number of hidden layers may significantly reduce performance of the ANN.

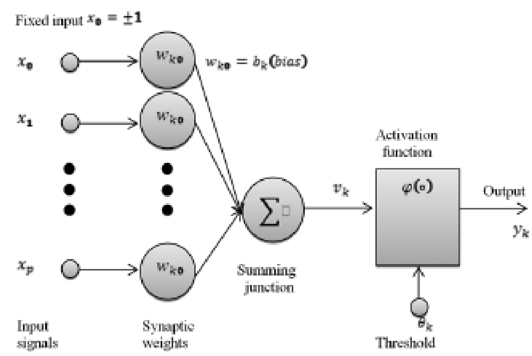

Figure 2.
Mathematical model of ANN [5]

3. SENSITIVITY ANALYSIS

3.1. Outline of sensitivity analysis

Sensitivity analysis (SA) is a typical statistic problem. In this paper, sensitivity analysis directly precedes the back analysis. This analysis shows the influence of the parameters on the structure displacements. The influence of Mohr-Coulomb model parameters (Young's modulus, cohesion and friction angle) is presented. It can be noticed that the sensitivity analysis gives really important information for numerical modelling. Different kinds of constitutive models behave in different ways which makes it hard to indicate the most sensitive parameters. Full knowledge of sensitivity will be indispensable in geotechnical designing in the future. It can be done by specific implementation in FE code or, as shown below, by using Artificial Neural Network.

In general, sensitivity of the interesting parameter can be represented by a composite scaled sensitivity, which is given by the equation [6]:

$$css_j = \left[\frac{1}{ND}\sum_{i=1}^{ND}\left(\left(\frac{\delta y`_i}{\delta b_j}\right) b_j \omega_{ii}^{\frac{1}{2}}\right)^2\right]^{\frac{1}{2}} \tag{1}$$

css_j – composed scaled sensitivity of the j^{th} parameter,

b_j – the j^{th} parameter being studied,

y_i – the i^{th} computed value,

$\frac{\delta y`_i}{\delta b_j}$ – sensitivity of the i^{th} computed value with respect to the j^{th} parameter

ω_{ii} – weight of the i^{th} observation,

ND – number of observations.

3.2. Input parameters used to create ANN for sensitivity analysis

Parameters used for input data describe the constitutive model of soil (Mohr-Coulomb model) and location of data reference points. Displacements of the reference points from the numerical model were used as a target (output layer). In most cases the picked data reference points overlapped with the nodes of tunnels lining meshes. There were around 600 reference points for the present case. Selection of parameters for creating the procedure of data fitting was taken from the results of SBP tests [14]. The created network was trained to adjust specific weights of connections between the nodes (neurons). Quality of results received from the Artificial Neural Network depends on the data which was used to train the network. A scheme of the described Neural Network is shown in Figure 3.

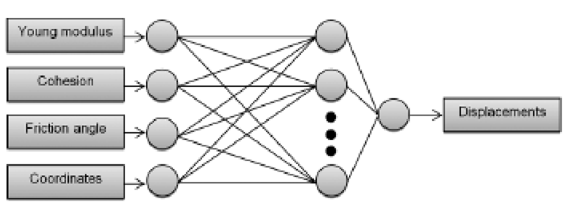

Figure 3.
Scheme of the ANN used in sensitivity analysis [1]

Specific data was used to ensure proper quality level of the Neural Network. Table 1 shows parameters sets of Törökbálint sandstone used in the analysis. The parameters are limited just to sandstone mainly because the tunnels are located in that kind of soil and it has the biggest influence on the structure. It is necessary to point out that the value of dilatancy angle was omitted for sandstone to reduce the number of output parameters.

Table 1.
List of parameters used to create the ANN for sensitivity analysis [1]

Parameters set	Modulus of elasticity E [kN/m²]	Cohesion c [kN/m²]	Friction angle Φ [°]
01 (initial)	24 000	100	36
02	12 000	100	36
03	80 000	100	36
04	24 000	400	36
05	24 000	0	36
06	24 000	100	45
07	24 000	100	5
08	160 000	100	36
09	24 000	1000	36

In present case training of ANN has insignificant influence on the results. Reason of this behaviour is connected with a huge number of reference points (input data) used to train Neural Network.

3.3. Artificial Neural Network in sensitivity analysis

The software used to create the neural network automatically creates several types of networks. Created networks differ from one another in a number of hidden layers and activation functions. For further analysis the network with the best performance was chosen by comparison of the correlation coefficient (r), Mean Squared Error (MSE) and Mean Absolute Error (MAE). The correlation coefficient equal to 1 says that the predicted value is equal to the computed value (target). Comparison of horizontal (DX) and vertical (DZ) displacements received from FEM and from trained ANN are shown in figure 4 and 5.

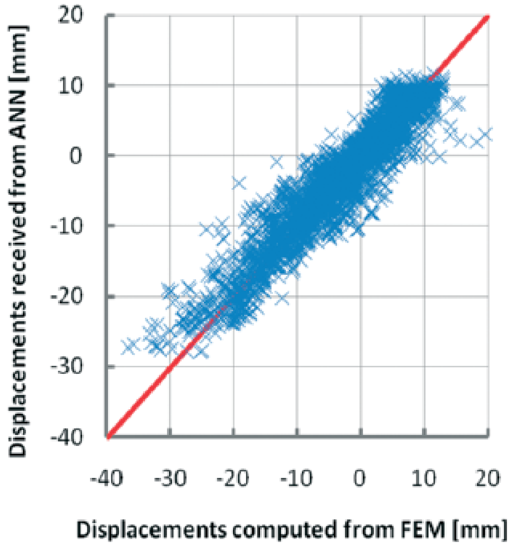

Figure 4.
Comparison of horizontal displacements (DX) received from FEM and from trained ANN [1]

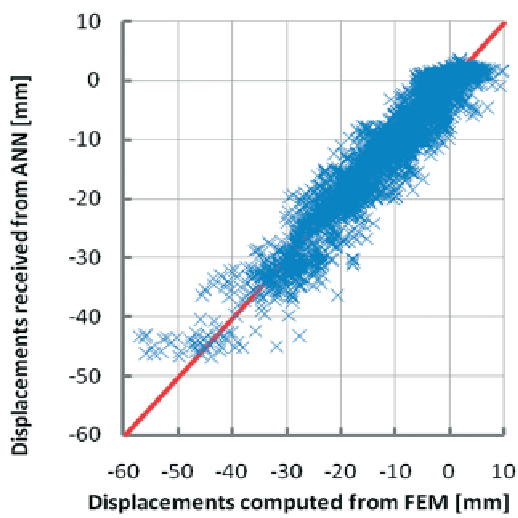

Figure 5.
Comparison of vertical displacements (DZ) received from FEM and from trained ANN [1]

3.4. Results of Sensitivity Analysis

Sensitivity analysis was performed separately for two main directions of displacements: horizontal (X-axis) and vertical (Z-axis). Third direction (Y-axis) which goes along the tunnels was not taken into consideration because these displacements have got insignificantly small influence. Except for the input parameters that describe the Mohr-Coulomb model sensitivity analysis includes coordinates (X, Y, Z) of the reference points. Sensitivity of these coordinates does not have any meaning because it describes a displacements change with respect to the position. The results of sensitivity analysis were summarized in Figure 6 for the South Tube and in Figure 7 for the North Tube.

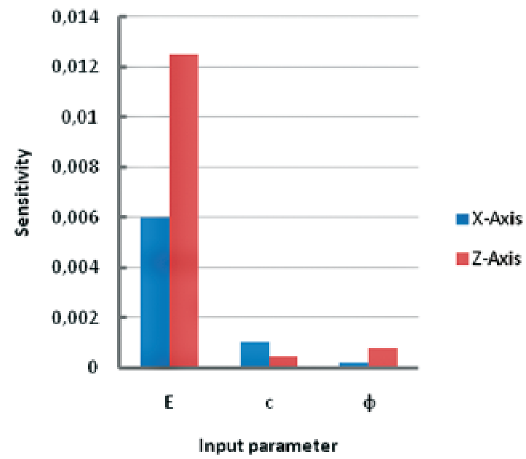

Figure 6.
Sensitivity of Törökbálint sandstone parameters for the South Tube [1]

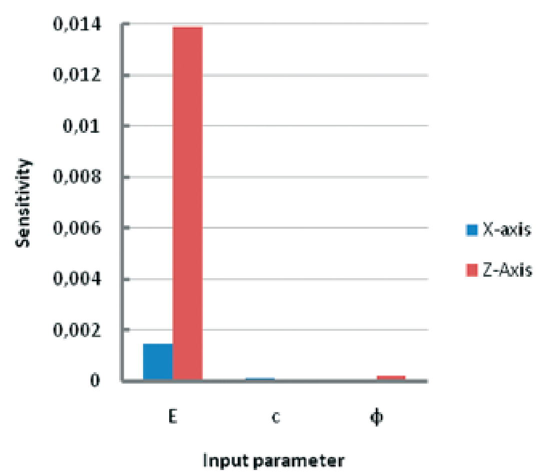

Figure 7.
Sensitivity of Törökbálint sandstone parameters for the North Tube [1]

It can be seen that sensitivity characteristics of the parameters which describe the constitutive model match the reality. Young's modulus has the biggest influence on the displacements, friction angle and cohesion have insignificantly small influence. Sensitivity parameters for both tubes are similar, the values of elasticity modulus for the North Tube are higher for vertical direction (Z-axis). For the South Tube elasticity modulus has bigger influence in horizontal direction (X-axis). Cohesion and friction angle have a comparable influence for both tubes.

4. BACK ANALYSIS

4.1. Introduction to back analysis

Back analysis can be solved by using two different methods: a direct and inverse method. The inverse method is a reversed ordinary stress analysis which can be applied to every kind of analysis, even in nonlinear back analysis. However, this method sometimes needs to deal with complex mathematical and programing background. Using direct method there is no need to deal with so difficult background as in case of the inverse method. In the direct method iterative process is used which minimizes the error level of a specific function that determines the quality of the results. In this paper direct method is proposed as an easy solution to perform back analysis [7].

Back analysis can be solved by using one of the following techniques:
- Mathematical algorithm,
- Artificial Neural Network,
- Genetic algorithm.

Back analysis using mathematical algorithms is the most widely developed field, it requires high level of knowledge and provides high reliability of the obtained results. This group of methods can be implemented into a finite element code. For years, back analysis procedures based on the mathematical algorithms were developed. They can be divided into two main groups [7]:
- Back-analysis in elasticity,
- Back-analysis in elasto-plasticity.

In contrary to the mathematical method, Artificial Neural Network and Genetic algorithm do not require such a wide mathematical and programming background. These methods use several trial runs to reach the expected level of the results quality. Based on good results these unconventional methods have recently gained popularity thanks to a development of technology.

Genetic algorithm method is based on Darwin's principle of survival of the fittest [8] which imitates evolution of population. The principle of this method is to create a new generation which will reach the expected level of quality. The new generation differs from the old generation by slightly mutated parameters. [9]

Artificial Neural Network serves to several trial runs which minimize the level of error function to the required level.

In general, there are several combinations of parameters which can be obtained [7]:
- Material parameters,
- Load parameters,
- Both material and load parameters,
- Geometry,
- Geometry and material,
- Geometry and load,
- Geometry, material and load.

4.2. Adopted Artificial Neural Network

The whole process of creating the Artificial Neural Network for back analysis is similar to the process applied in the sensitivity analysis.

Displacements from each construction stage obtained from the reference points and localization of these points were used as input parameters. In contrary to the sensitivity analysis, to train the network as a target layer (further output layer), parameters which describe the constitutive model (with respect to depth) were used. Specific weights of connections between the nodes (neurons) were adjusted after network training.

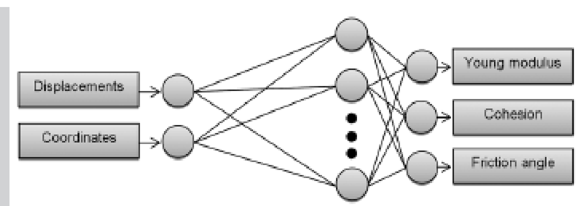

Figure 8.
Scheme of the Artificial Neural Network used in back analysis [1]

A scheme of the Artificial Neural Network used to create the network is shown in Figure 8. However, presented scheme can be modified by increasing number of input parameters. For example, construction stages, characteristics of the tunnel lining, excavation area, etc. might be also included. In this case quality and reliability of the results can increase significantly.

Comparison of data used to create the Artificial Neural Network to the data obtained from the created ANN is shown in Figure 9. It can be noticed, that each displacement curve on the inclinometer coincides with the curve obtained from ANN. The curves of vertical displacements for E=24000 kN/m^2 and 12000 kN/m^2 shows the highest convergence. The lowest convergence is exhibited by the curve for E=80000 kN/m^2. With an increase of the value of elasticity modulus the curves obtained from ANN have lower quality and show tendency to wave. However, they still have an acceptable quality level of results.

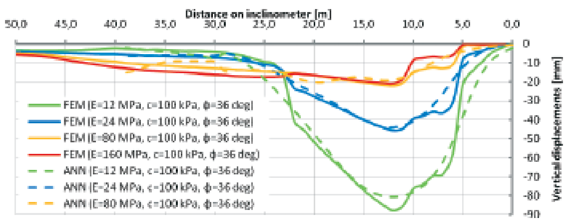

Figure 9.
Comparison of displacements obtained from FEM and from ANN (North Tube) [1]

Additional quality check of the created Artificial Neural Network was performed. The correlation of vertical displacements received from the FEM and ANN analyses performed for the location of inclinometer above North Tube is shown in Figure 10. The correlation coefficient was used to choose a neural network. The network with the highest level of correlation was chosen for further analysis.

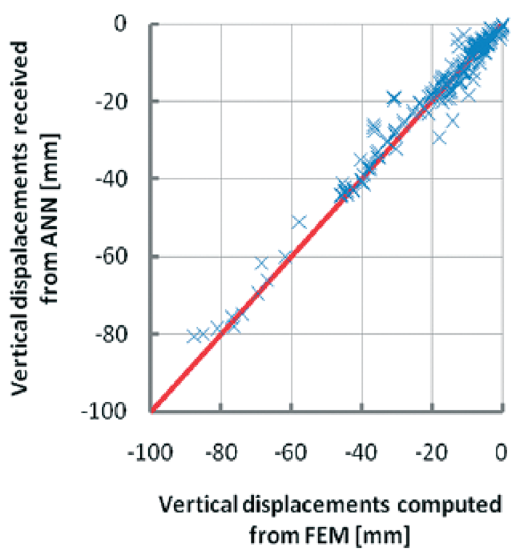

Figure 10.
Correlation of vertical displacements (DZ) received from FEM and ANN analyses performed for the location of inclinometer above North Tube [1]

4.3. Validation method

An appropriate level of accuracy can be defined by means of a specific error function. Error function is the determinant of an optimization process of the created network and used input parameters. Specific function used in the analysis is described by Eq. (2) [10]:

$$\varepsilon = \sum_1^m \left(u_i - u_{i_m}\right)^2 \tag{2}$$

ε – error function,

u_j – the i^{th} predicted value of performance,

u_{jm} – the corresponding i^{th} value of measured performance.

Reliability of results can be improved by including weight of each observation, which is much closer to description of real conditions. Weights are often related to reliability and quality of data measurements, for example deformation of the tunnel lining could be more reliable than the measured stresses in the lining. The described modification is presented by Eq. (3) [10]:

$$\varepsilon = \sum_1^m \left\{ w_i \cdot \left(\frac{u_i - u_{i_m}}{u_{i_m}}\right)^2 \right\} \tag{3}$$

w_i – weight factor applied for each measurement.

Above-mentioned functions are highly non-linear and computation time may rise with an increasing number of parameters. For further considerations, error function without weights factors was adopted, which is presented by Eq. (2) [10]. The results collected in Table 2 present the error level for each displacement curve for specific parameters obtained from ANN. Additionally, the error level of the whole ANN, which is equal to 0.00198, was presented.

Table 2.
Error level of specific curves obtained from ANN [1]

E [kN/m^2]	c [kN/m^2]	Φ [°]	ε
12000	100	36	0.00117
24000	100	36	0.000351
80000	100	36	0.000456
			Σ = 0.00198

4.4. Result of back analysis

The final set of parameters obtained from the back analysis, is listed below:

– Modulus of elasticity E=45000 kN/m^2

– Cohesion c=240 kN/m^2

– Friction angle Φ=36°

There are also additional parameters which were not included in the back analysis but are essential to describe the behaviour of soil in the numerical model:

– Increment of elastic modulus 14500 kN/m^3

– Increment of cohesion 112 kN/m^3

Comparison of the elasticity modulus and cohesion is shown in Figure 11 and 12, a curve obtained from Self Boring Pressuremeter (SBP) is close to the real conditions. Data from geotechnical design presents a constant value of the elasticity modulus and cohesion without taking into consideration the influence of depth. In most cases it is sufficient to omit this factor but in back analysis and with complex geotechnical conditions it can lead to overestimation of stresses and displacements. The value of the parameter obtained from Artificial Neural Network has similar characteristics to the data presented by SBP, however, the value is higher which is probable. The reason of similar characteristic is that the influence of depth on the elasticity modulus and cohesion were included in the material properties.

Soil parameters chosen as the final are probable and reasonable with high convergence level with the real conditions (Self Boring Pressuremeter). Comparison of displacement curves being a result of new soil parameters are shown in Figure 13 for the North Tube and in Figure 14 for the South Tube. In wider consideration the back analysis of the increment of the elastic modulus and cohesion should be performed.

It can be seen that the curve of displacements for a new set of parameters (from back analysis) on the inclinometer above the North Tube fits well enough to the curve from monitoring data. Displacements curve for the inclinometer above the South Tube for a new set of parameters is much different and not comparable to curve obtained from geotechnical monitoring. Displacement curve from numerical model is much higher; the reason is that back analysis was performed to fit displacements on the North Tube. The error level for both tubes is presented in Table 3 confirms previous observations.

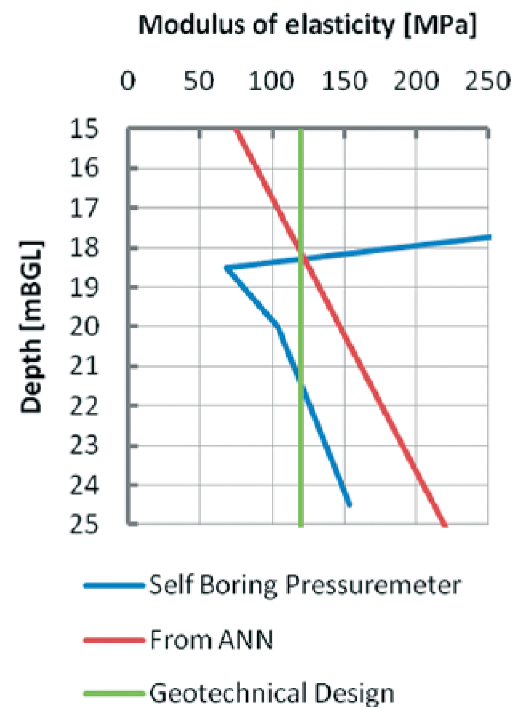

Figure 11.
Comparison of modulus of elasticity obtained from different sources [1]]

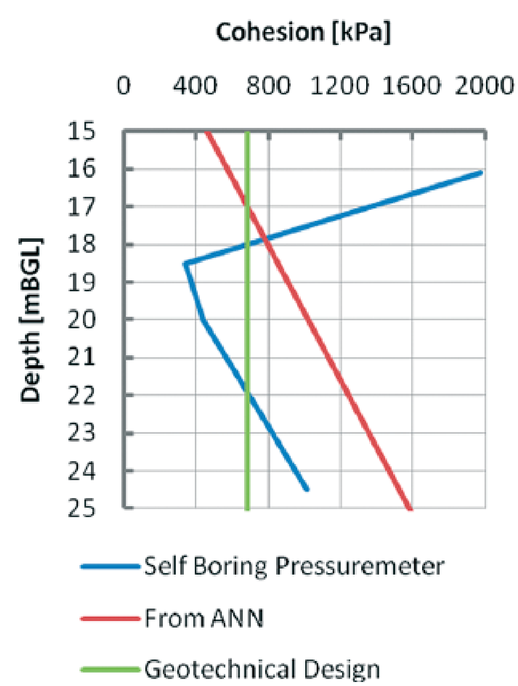

Figure 12.
Comparison of cohesion obtained from different sources [1]

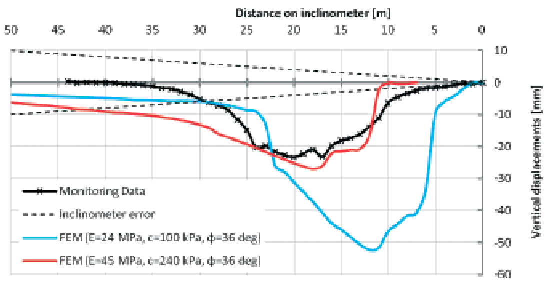

Figure 13.
Comparison of displacements obtained from inclinometer and FEM after back analysis (North Tube) [1]

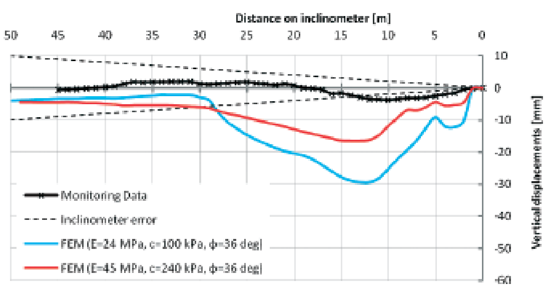

Figure 14.
Comparison of displacements obtained from inclinometer and FEM after back analysis (South Tube) [1]

Table 3.
Error level of specific curves after back analysis [1]

Localization	E [kN/m²]	c [kN/m²]	Φ [°]	ε
North Tube	45000	240	36	0.00347
South Tube	45000	240	36	0.03727

5. CONCLUSIONS

The presented method of using Artificial Neural Network in the back analysis has many advantages, especially in prediction of soil parameters which is a very difficult task.

As a result of sensitivity and back analyses based on the Artificial Neural Network, the following conclusions can be presented:

- Back analysis with the use of the Artificial Neural Network provides good results and in the future can replace traditional mathematical techniques,
- This method is easy to apply in every geotechnical problem without necessity to have a wide mathematical and programming background,
- Presented method requires high-quality level of a numerical model, which directly affects the site investigation. Quality of back analysis rises significantly with the quality of numerical model which in effect decreases the final number of finite element runs,
- Artificial Neural Network used in back analysis, needs relatively few FEM calculations (about 10 times or even less) in comparison to the traditional method (sometimes 100-200 times). FEM calculation in back analysis with use of ANN serves to obtain specific behaviour of a numerical model which will allow to fit soil parameters. Back analysis with use of traditional methods requires high number of finite element calculations for fitting the numerical model. This advantage drastically decreases the time of computation,
- Artificial Neural Network requires relatively high amount of data from the numerical model to ensure the proper quality and behaviour of the obtained parameters,
- Artificial Neural Network can take into account many significant factors, as the level of reliability (accuracy) of conducted data from geotechnical monitoring,
- There is a possibility to build an ANN without creating a numerical model. ANN can be based only on the data obtained from monitoring; however, it is a very difficult task and requires further development of this method.

ACKNOWLEDGEMENTS

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