# APPLICATION OF BACK ANALYSIS FOR SPRAYED CONCRETE LINED TUNNELS BUILT IN COMPLEX SUBSOIL CONDITIONS

Maciej Ochmański[1], Tibor Horváth[2]

[1] *The Silesian University of Technology, Gliwice, Akademicka 5, 44-100, Poland*
[2] *Geovil Ltd., Szentendre, Ady Edre 44/b, 2000, Hungary*

**KEYWORDS**
Sprayed Concrete Lined tunnels, Back Analysis, Artificial Neural Network.

## 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 (Geovil Ltd., 2005, 2008a, 2008b, 2009).

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 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 difficult to obtain with use of traditional methods. In this paper Artificial Neural Network (ANN) was used to perform back analysis.

## NUMERICAL MODEL

To create finite element model and carry out the analysis Midas GTS 2011 (v1.1) software was used. Numerical model was created as a three dimensional model which consisted of around 100 000 tetrahedral four-node finite elements. The mesh was automatically generated by Midas GTS as a tetrahedral solid mesh, with variable sizes in smooth transition. Quality of the finite element mesh is presented in Figure 1a for the whole generated mesh and in Figure 1b for the tunnels mesh. The following assumptions have been considered during modelling process:

- Soil behaviour was modelled using a nonlinear constitutive Mohr-Coulomb model. Two variants of parameters were assumed: in the first variant the parameters were the same as in the structural design project (without including change of the parameters with depth); in the second variant they were determined with Self Boring Pressuremeter (SBP) test (which included change of the parameters with depth),
- To adjust boundary conditions specific model was prepared with fully excavated tunnels without any support (tunnel lining). For the matching initial boundary conditions recommendations from Kolymbas (2003) were used,
- Numerical model did not include the structure of the whole station, only the SCL Tunnels and western part of the diaphragm wall were modelled. To include stiffness of the whole station, nodes which represent slab above and under the tunnels were additionally restrained in vertical direction,

- Tunnels lining was modelled as a two dimensional (2D) structure which reduced complexity and computation time,
- Due to the lack of visco-elastic “Kelvin” creep model (which is the most suitable model) behaviour of shotcrete was modelled by using the simplest constitutive model - linear-elastic model with age-dependent stiffness,
- The model of thin layer with different material properties representing a fault zone was applied in the numerical model. Only fault zones close to the tunnels were modelled because the influence of other faults was marginal,
- Soil strengthening (freezing, grouting) were included as local material parameters change of finite elements. It was not necessary to model the geometry of the improved zones, because the real zone of the influence depends on many variables and can be difficult to estimate,

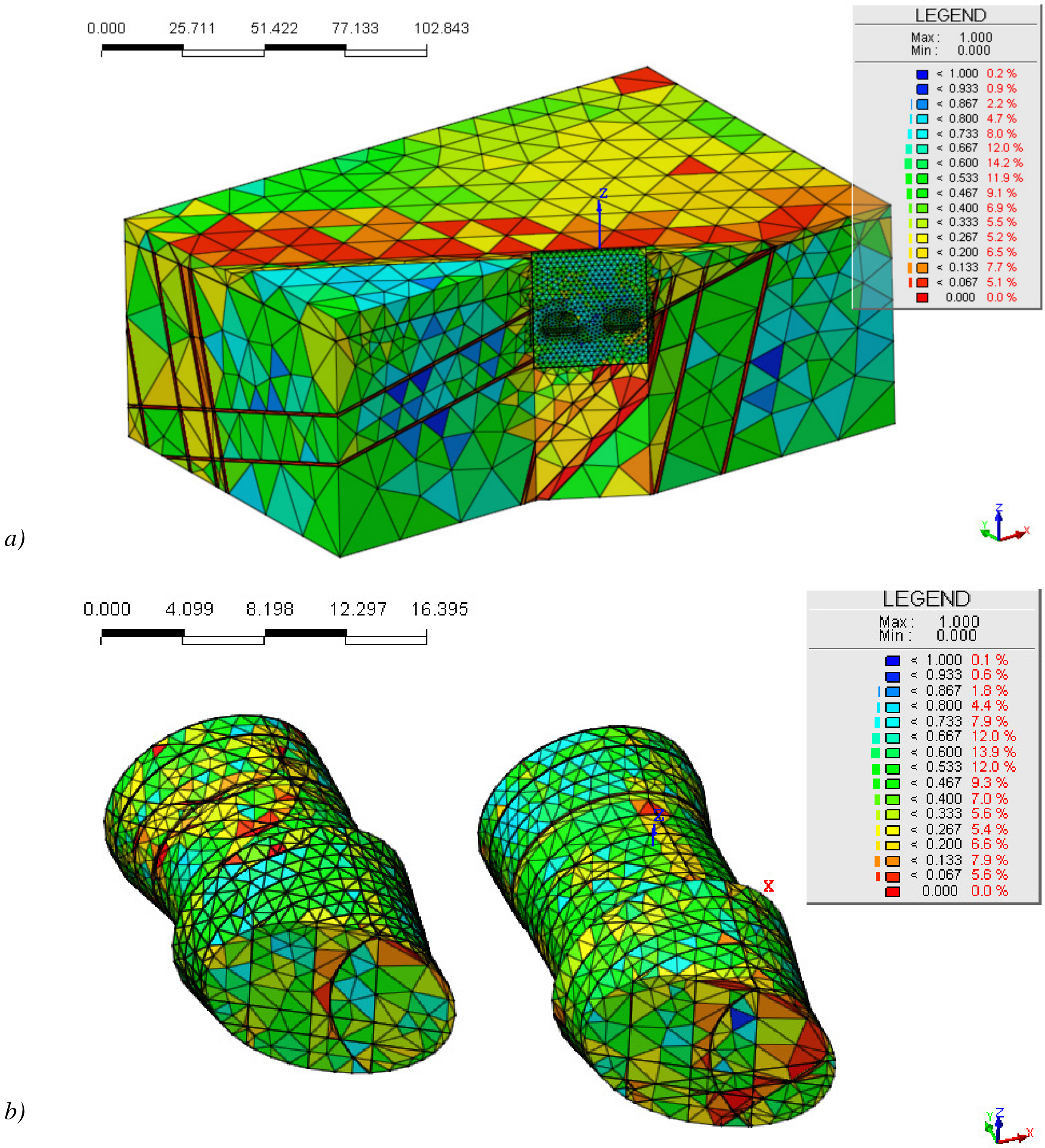


*Figure 1: Quality of generated mesh: a) Mesh of whole model, b) Mesh of SCL Tunnels (Ochmański, 2012)*

– The whole construction process was divided into a number of construction stages according to the structural design. To ensure the required level of accuracy, all significant excavation/construction steps were considered (side drift, enlargement, drilling chamber, backfill etc.).

## BACK ANALYSIS

*Introduction*

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 laboratory. Due to this fact it is reasonable to perform back analysis.

In this paper, the Artificial Neural Networks (ANN) were used to perform sensitivity analysis and back analysis. ANN is a method which simulates a human brain neural system. From the engineering point of view, Artificial Neural Network is a perfect method which is characterized by very short computation time, simplicity in application in almost every kind of analysis and, the most important, reliability of results that is shown in further considerations.

*Sensitivity analysis*

Sensitivity analysis (SA) is a typical statistic problem. 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. In general, sensitivity of the interesting parameter can be represented by a composite scaled sensitivity, which is given by the equation (Lippmann, 1987):

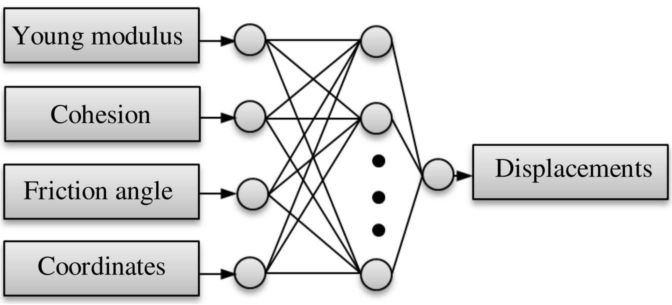


*Figure 2: Scheme of the ANN used in sensitivity analysis (Ochmański, 2012)*

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

$css_j$ – 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
$\omega_{ii}$ – weight of the $i_{th}$ observation,
ND – number of observations.

Parameters used for input parameters describe the constitutive model of soil and location of data reference points. Displacements of the reference points from the numerical model were used as a target (output layer). Different sets of parameters of Törökbálint sandstone were used to ensure proper quality level of the Artificial Neural Network. The parameters were limited just to sandstone mainly because the tunnels are located in that kind of soil and it has the biggest influence on the structure. The created network was trained to adjust specific weights of connections between the nodes (neurons). In most cases the picked data reference points overlapped with the tunnels lining. 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 Artificial Neural Network is shown in Figure 2.

The software used to create the artificial 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).

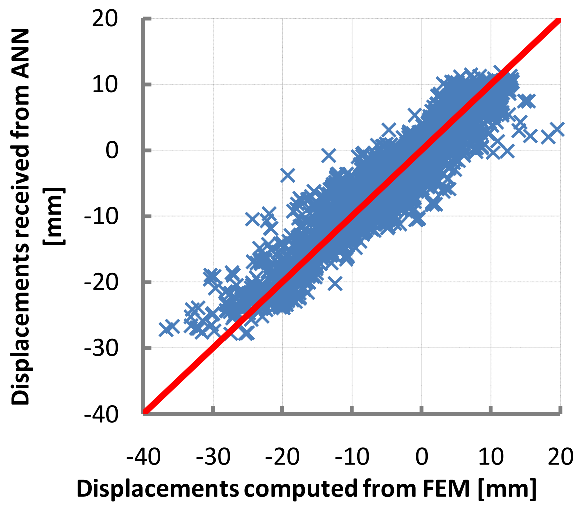


*Figure 3: Comparison of horizontal displacements received from FEM and trained ANN (Ochmański, 2012)*

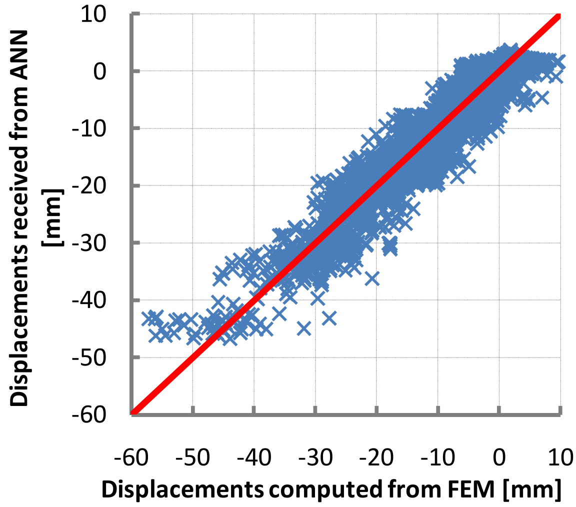


*Figure 4: Comparison of vertical displacements received from FEM and trained ANN (Ochmański, 2012)*

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 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 5 for the South Tube and in Figure 6 for the North Tube.

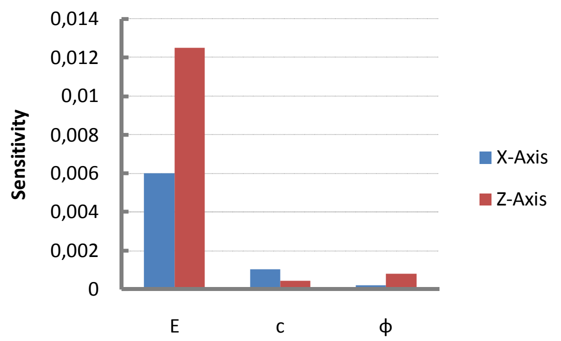


*Figure 5: Sensitivity of Törökbálint sandstone parameters for the South Tube (Ochmański, 2012)*

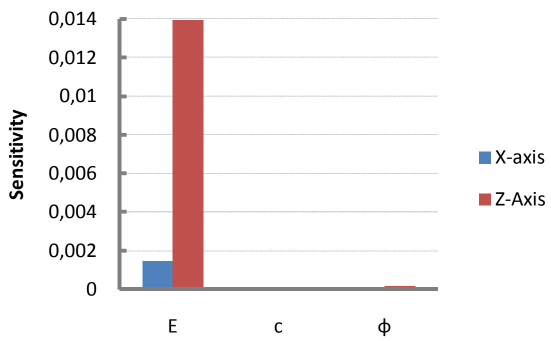


*Figure 6: Sensitivity of Törökbálint sandstone parameters for the North Tube (Ochmański, 2012)*

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 an insignificantly small influence. Sensitivity parameters for both tubes are similar.

*Back analysis*

Back analysis can be solved by using two different methods: a direct or inverse method. The inverse method is a reversed ordinary stress analysis which can be applied to every kind of analysis, even in non-linear back analysis (Akutagawa, 1991). 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.

Back analysis can be solved by using one of the following techniques:

- Mathematical algorithm,
- Artificial Neural Network,
- Genetic algorithm.

In this paper the Artificial Neural Network was used to perform back analysis. 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.

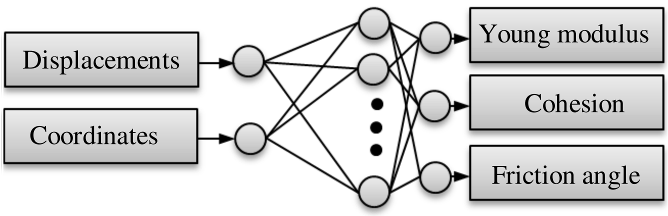


*Figure 7: Scheme of the ANN used in back analysis (Ochmański, 2012)*

A scheme of the ANN used to create the network is shown in Figure 7. 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 (from FEM) used to create the Artificial Neural Network to the data obtained from the created ANN is shown in Figure 8. It can be noticed, that each displacement curve on the inclinometer coincides with the curve obtained from ANN. 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.

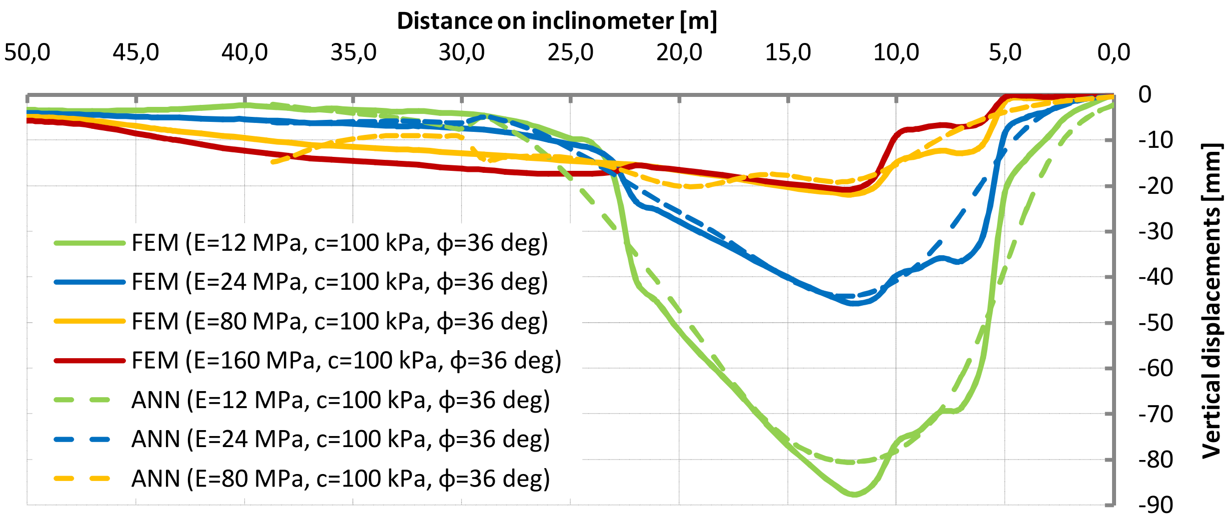


*Figure 8: Comparison of displacements obtained from FEM and ANN (North Tube) (Ochmański, 2012)*

Additionally, quality check of the created Artificial Neural Network was performed. 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 of vertical displacements between the FEM and the ANN is shown in Figure 9.

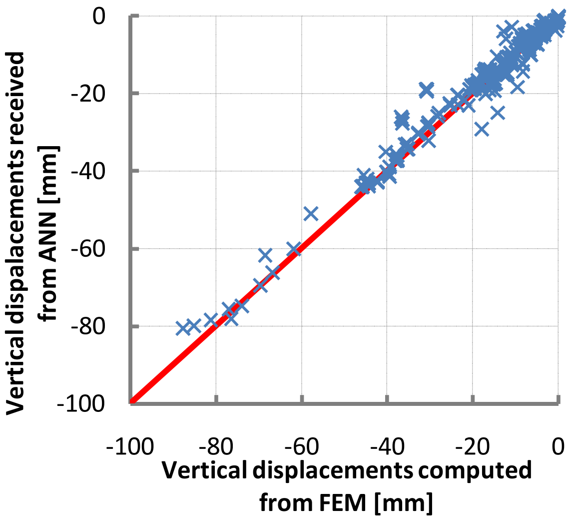


*Figure 9: Correlation of vertical displacements between FEM and ANN (Ochmański, 2012)*

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 equation (Vardakos, 2007):

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

$\varepsilon$ – error function,
$u_i$ – the $i_{th}$ predicted value of performance,
$u_{im}$ – 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.

*Table 1: Final Törökbálint sandstone parameters*

| Parameters obtained from back analysis | |
|---|---|
| Modulus of elasticity [E] | 45 000 kN/m$^2$ |
| Cohesion [c] | 240 kN/m$^2$ |
| Friction angle [$^o$] | 36$^o$ |
| Additional essential parameters which were not included in the back analysis | |
| Increment of Elastic Modulus | 14 500 kN/m$^2$ |
| Increment of Cohesion | 112 kN/m$^2$ |

*Results*

Comparison of the elasticity modulus and cohesion is shown in Figure 10 and 11, 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. 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.

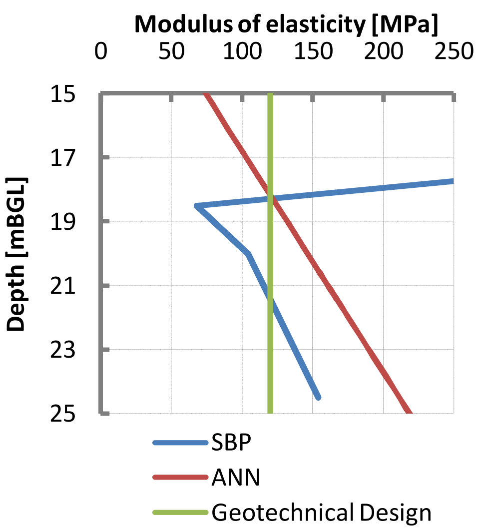


*Figure 10: Comparison of modulus of elasticity obtained from different sources (Ochmański, 2012)*

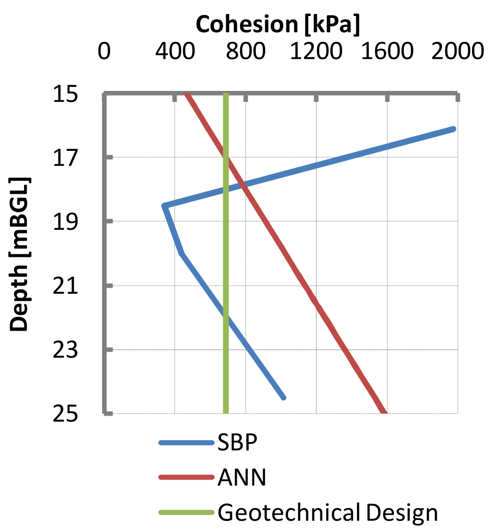


*Figure 11: Comparison of cohesion obtained from different sources (Ochmański, 2012)*

The Final soil parameters obtained from back analysis 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 12 for the North Tube and in Figure 13 for the South Tube.

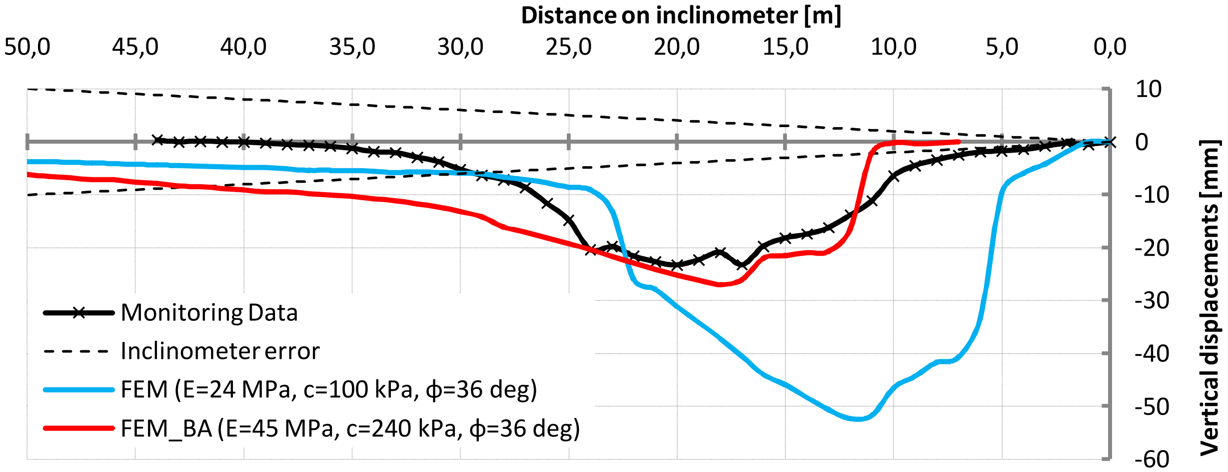


*Figure 12: Comparison of displacements obtained from inclinometer and FEM after back analysis (North Tube) (Ochmański, 2012)*

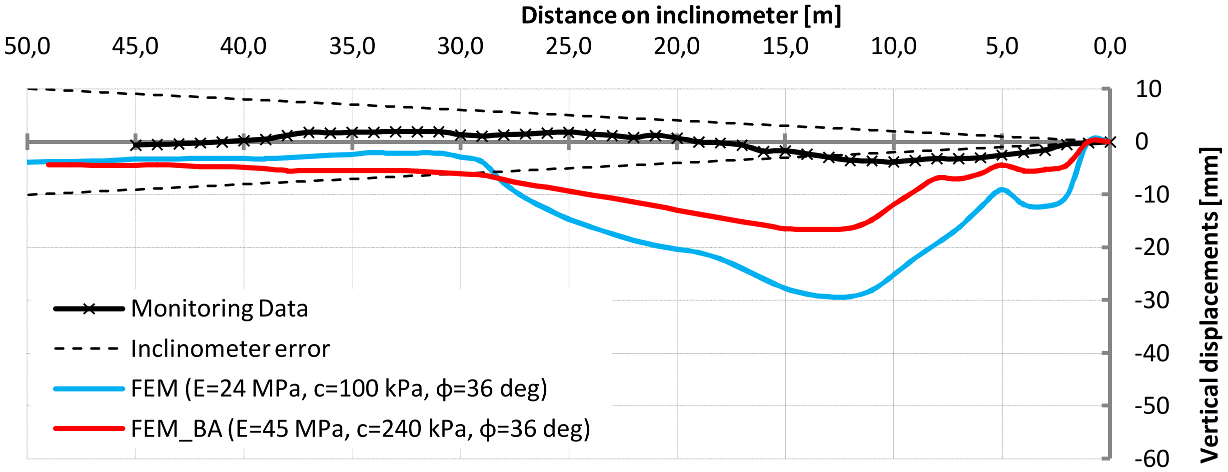


*Figure 13: Comparison of displacements obtained from inclinometer and FEM after back analysis (South Tube) (Ochmański, 2012)*

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.

## CONCLUSIONS

Sprayed Concrete Lined (SCL) tunnels are sophisticated structures which require comprehensive approach. The best estimation of soil parameters was provided by Self Boring Pressuremeter. These parameters have been used to create a numerical model. They take into account change of the modulus of elasticity and cohesion with depth. The structure and soil behaviour obtained from the numerical model is similar to the behaviour presented by geotechnical monitoring which prove reliability of the numerical model. Concluding, the created model can be used in a structural design.

However, the results can be overestimated because variable value of $K_0$, which in nature increases with depth, was not considered.

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 analysis and back analysis based on the Artificial Neural Network, the following conclusions can be presented:

- Back analysis with 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),
- 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.


## ACKNOWLEDGEMENTS

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## REFERENCES


Akutagawa, S. (1991), *A back analysis program system for geomechanics applications*, University of Queensland, Queensland.

Kolymbas, D. (2003), *Rational Tunnelling. Advences in Geotechnical Engineering and Tunnelling.* Innsbruck: Logos Verlag Berlin.

Lippmann, R. (1987), *An introduction to computing with neural nets.* IEEE ASSP Magazine, 4, 4-22.

Ochmański, M. (2012), *Application of back analysis for Sprayed Concrete Lined tunnels built in complex subsoil conditions,* MSc thesis, The Silesian University of Technology, Gliwice

Vardakos, S. (2007), *Back-analysis Methods for Optimal Tunnel Design*, PhD thesis, Virginia Polytechnic Institute and State University, Blacksburg.

Geovil Ltd. (2005), *Section 1 of Line #4 of the Budapest Metro Summary Expert Opinion on engineering, hydrogeological and geotechnical issues,* Szentendre.

Geovil Ltd. (2008a), *Budapest 4. metróvonal I. szakasz - Föväm tér állomás. Geotechnikai adatlapok az alagútépítés során készített talajszelvényezés felvételi lapjai (Section I of Metroline #4 of Budapest Fővám Square Station. Geotechnical Data Sheets prepared during construction of the tunnels).* Szentendre.

Geovil Ltd. (2008b), *Section I of Metroline #4 of Budapest Fővám Square Station. Geotechnical Construction Design for designing the station's space to be built using mining methods.* Szentendre.

Geovil Ltd. (2009), *Budapest 4. metróvonal I. szakasz, Fővám tér állomás bányászati módszerrel épített Ny-i oldali peronalagutak összefoglaló jelentés az építés geotechnikai viszonyairól (Section I of Metroline #4 of Budapest Fővám Square Station. Geotechnical Summary Report for tunnels to be built using mining methods).* Szentendre.