

Use of artificial neural networks for the prediction of tunnelling-induced ground movements in urban area

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ABSTRACT

The main goal of this specific study is to reveal the benefits from the use of the ANN in geotechnical engineering by focusing on the elaboration of data coming from real field measurements concerning ground movements due to tunnelling. Moreover, the Back Propagation algorithm is used so as to reveal the hierarchy of each of the parameters mainly affecting the total amount of the induced settlements due to tunnelling. The short review of our experience in applying ANN's in Geotechnical Engineering is succeeded by the main accomplishments of this study. The provided information, originally published by Attewell, concerns tunnel size and depth, maximum settlement, settlement trough width, volume and slope, ground description, geological properties and excavation method.

1. INTRODUCTION

It is a challenging task to efficiently simulate site specific geological conditions and following the appropriate design approach, in order to successfully eliminate the possibility of failure, adopting a cost-effective design. Jing (2003) presented a flowchart of rock mechanics modelling and rock engineering design approaches. In “Figure 1” a categorization into eight approaches of modelling within the framework of a project objective is illustrated. There are two levels of “mapping”. The Level “1” includes methods attempting a 1:1 mechanism mapping, that is, an attempt of modelling geometry and physical mechanisms directly, either specifically or through equivalent properties (Jing 2003). Conversely, Level “2” includes methods in which such a mapping mechanism is not totally direct, e.g. the rock mass classification systems. The neural network method is a “non 1:1 mapping”, located in boxes 2C and 2D as indicated in “Figure 1” with grey pattern (Ferentinou and Sakellariou, 2007).

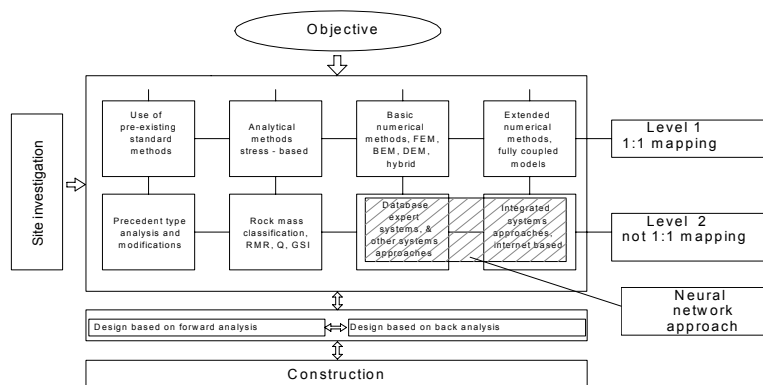


Figure 1: The four basic methods, presented in two levels which comprise eight different approaches to rock mechanics modeling (Jing 2003), (Ferentinou and Sakellariou, 2007).

Complex geomechanics systems are ideal for the application of computational intelligence methods, as the physical problem is often described by nonlinear relationships, which lead to the use of nonlinear transformation functions. However, this is not an easy task and requires experience, deep knowledge of engineering and a sufficient number of data. Sakellariou and Ferentinou (2005), Ferentinou (2004) and Ferentinou and Sakellariou (2007) have applied ANN's in the highly complex problem of estimating the stability of Soil and Rock Slopes. In that topic only a rough description of the physical and geometric characteristics of the slope is usually available and it is hard to determine representative values of the parameters involved in the problem, i.e. physical properties, strength parameters and geometry.

In a previous study, Neupane and Adhikari (2006) developed a back propagation NN to predict the ground behaviour around soft ground tunnels obtaining promising results. They used 20 data with 6 inputs and one output for the learning process and 20 data to test the trained NN.

In the present study, we apply back propagation algorithm to challenge the neural network using a set of 65 data coming from different types of ground profiles and referring to tunnels constructed with different methods of excavation. Our intention was to observe the behaviour of ANN in the learning stage. From our experience with slopes (Sakellariou and Ferentinou, 2005) and (Ferentinou,2004) the ANN has the ability to identify subsets of the data set which are of different "quality". By saying "quality", we not only mean good data but, also, we mean a data set containing different classes of data. In the case of slopes in particular, although the ANN's performance was very good according to the mean squared error "mse", the predicted values for a specific number of data vectors were not satisfactory. The network recognized a different trend in these vectors differing from the majority of data.

2. ARTIFICIAL NEURAL NETWORKS

2.1 General background

Artificial neural networks (ANN) are computer based models inspired by the structure and behaviour of real biological neurons whose architecture mimics the knowledge acquisition and organizational skills of the human brain cells. They consist of numerous simple processing units, the "neurons", which can globally be programmed for computation. They can be trained to store, recognize, and associatively retrieve patterns or database entries from large data sets, to solve large optimization problems. In summary, they constitute model free estimators of continuous functions (Han, 2000).

Artificial neural systems recognize patterns that we cannot even define. This property is called recognition without definition. Concepts such as a tree or a face are not learned through a definition. We learn these concepts in a descriptive mode by pointing out examples. Recognition without definition is a characteristic of intelligent behaviour and enables systems to generalize.

ANNs are also interpreted as simple input-output functions that act as threshold switches for continuous neurons. The neurons are logically arranged in two or more layers and interact with each other via weighted connections. These scalar weights determine the nature and strength of the interaction between the interconnected neurons. Neural networks essentially learn through the adaptation of their connection weights.

2.2 Data analysis using feed forward Multi-Layer Perceptron (MLP) – Back Propagation (BP)

The BP algorithm is a non linear extension of the Least Mean Squares (LMS) algorithm for multilayer perceptrons. It is the most widely used of the neural network paradigms and was successfully applied in many fields of model free function estimation. The BP algorithm begot criticism concerning its

ability to converge. Convergence to a particular solution takes a long time, especially during the training process. Properly trained back propagation networks (BPN) tend to produce reasonable results when presented with new data set inputs. In MLPs, the learning process is achieved by adjusting weights in the network until a particular input leads to a specific target output.

A simple type of multilayer perceptron consists of three layers: the input layer, the hidden layer, and the output layer, as depicted in the following “Figure”. BPN is usually layered, with each layer fully connected to the layers below and above. The first layer is the input layer, the only layer in the network that can receive external input. The second layer is the hidden layer in which the processing units are interconnected to layers below and above. The third layer is the output layer. Each unit of the second hidden layer is interconnected to the units in the output layer. Units are not connected to other units in the same layer. Each interconnection has associative connection strength, depicted as weight in the following “Figure”. Weights are adjusted during training of the network. In BPN training is supervised; the network is presented with target values for each input pattern.

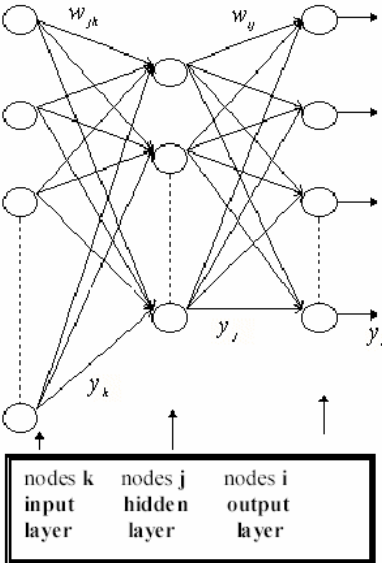


Figure 2: Architecture of a generalised multilayer perceptron.

2.3 Hierarchy of the involved parameters - Partitioning of connection weights through BP

It is an issue of paramount importance for the geotechnical engineers to be able to distinguish the parameters mainly affecting the tunnelling induced settlements from the ones of minor influence, and determine their relative importance. The procedure followed is based on an objective and systematic method, the method of the partitioning of connection weights proposed by Garson (1991) and adopted by Goh (1995), by Sakellariou and Ferentinou (2005) and Ferentinou and Sakellariou (2007).

3. APPLICATION OF THE BACK PROPAGATION ALGORITHM FOR THE CLASSIFICATION OF DATA

The main goal of this specific study; is to reveal the potential ability of a training procedure of an ANN to distinct data of different “quality” by using the back propagation algorithm. The term “quality” of data refers to the geological conditions and the excavation method applied in each case. As far as the geology is concerned, the available information is deficient. Nevertheless, according to a specific procedure analytically presented in the following relevant paragraphs, a primary distinction of them, in homogeneous and heterogeneous data, became feasible. Generally, the parameters which can differentiate the available data according to their “quality” characteristics, concern the geology and the excavation method.

Moreover, it is important to highlight that this procedure resulted in the classification of the available data according to their “quality”, without the application of any unsupervised encoding, such as the self organizing maps (SOM algorithm) (Kohonen, 1995).

3.1 Short description of the training procedure and the confronted difficulties

In our study, artificial feed-forward neural networks were developed and a relevant code was written in MATLAB. The scope was to investigate the accuracy and flexibility of the method to the specific real-world data sets. Main goal of this study is to explore the data set, test their quality and to investigate the relative importance of the input parameters using the method of partitioning of connection weights, presented in §2.3.

The total amount of the available data is 65 records. In the first attempt for the training of the ANN, all the available data were included. The tunnel depth and diameter have been used as input data and the surface settlement as output. It must be noted that information such as the geological conditions and the excavation method were not initially taken into consideration.

Even though the architecture of the ANN was formulated according to the same rules as the ANN used in former studies Sakellariou and Ferentinou (2005) and Ferentinou and Sakellariou (2007), the training of the ANN could not be accomplished.

When the training of the ANN fails, the questioning concerning the potential reasons for this unsuccessful attempt is inevitable. Nevertheless, no optimization of the ANN architecture takes place without having first excluded the possibility of any adverse impact of a physical problem, causing incompatibility in the training data.

The interpretation of the results and observation of their training quality became urgent. The training data which seemed not to be able to fit in the training procedure were spotted and excluded. As the training of the ANN was still unattainable there was a necessity for further measures to be taken. In this direction, a separation of data in homogeneous and heterogeneous, according to geology, took place. For the separation of data, Jeffery’s approach was used. Jeffery (1920), calculated the displacements and the stresses in an elastic half plane, caused by a uniform radial tensile stress q at the boundary of a circular cavity of radius r , having its center at a depth h below the flat horizontal boundary $y=0$ of the half plane. Verruijt (1998) presented a method based on Muskhelishvili’s complex variable method, using conformal mapping of the elastic region onto a circular ring, and developed a program to facilitate its use.

In a previous study (Statha, 2006), was shown that as far as homogeneous formations are concerned, their behaviour can be described / predicted efficiently by the use of the Jeffery’s solution. On the contrary, the specific solution cannot be applied in cases of tunnelling in heterogeneous formations.

According to the above mentioned and by using the program developed by Verruijt (2006), the classification of data in two groups (homogeneous and heterogeneous geological formations) became feasible.

The separation of data according to their geology had fruitful impacts in their training, as it made it feasible. The tunnel depth and diameter have been used as input data and the surface settlement as output.

Up to this point, the “parameters” geology and excavation method were not taken into account as input data in the training procedure. As their impact in the induced settlements is well known, in the third stage of the training procedure, four parameters were used as input data (tunnel depth, diameter, geology and excavation method) and one as output (surface settlement).

The training of the ANN was immediate and only a few records were excluded from the training procedure as extreme values. It is reminded that in this stage, the training of the ANN became feasible even if both homogeneous and heterogeneous formations were put together. In the previous stage, where only the tunnel depth and diameter were used as input data, the training of the ANN was attainable only after the separation of the data in two groups according to their geology. This remark reveals the necessity for the “parameters” geology and excavation to be taken as input data in the training procedure.

So, it is well understood that there is no reason putting all the available data together, unless we include the geology and the excavation method in the input data. This is a remark of great significance, as it reveals the importance of each component of the training data.

3.2 Presentation and evaluation of the results – Application of the method of the partitioning of connection weights

After the training of the ANN was accomplished, the procedure shortly mentioned in §2.3 was followed in order to determine the hierarchy of the included parameters and thus their contribution to the induced settlements. This is the method of partitioning of weights and it was applied to the last (third) training stage, in which four parameters were used as input data (tunnel depth, diameter, geology and excavation method) and one as output (surface settlement).

The results are given in the following “Figure 3”. Additionally, the corresponding Figure (“Figure 4”), concerning the relative importance of the parameters contributing to slope stability in circular failure mode (training set included 52 cases), coming from a previous study (Ferentinou and Sakellariou, 2007), is also apposed. The input data for slope stability estimation consist of values of the following input parameters: unit weight γ , cohesion c , angle of internal friction ϕ , slope angle β , height H , and pore water pressure ratio r_u , for soil or highly fractured rock slopes. As an output, the networks estimate the factor of safety F that can be modelled as a function approximation problem.

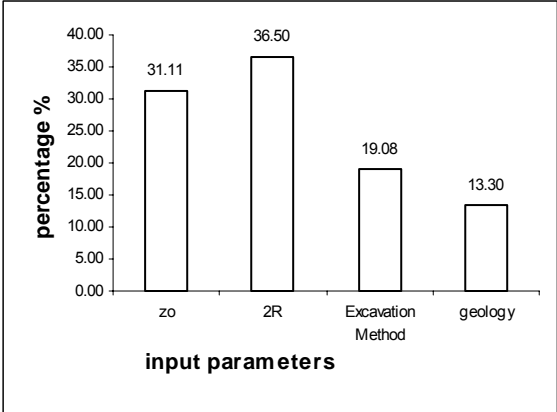


Figure 3: Relative importance of the parameters contributing to induced settlements due to tunnelling.

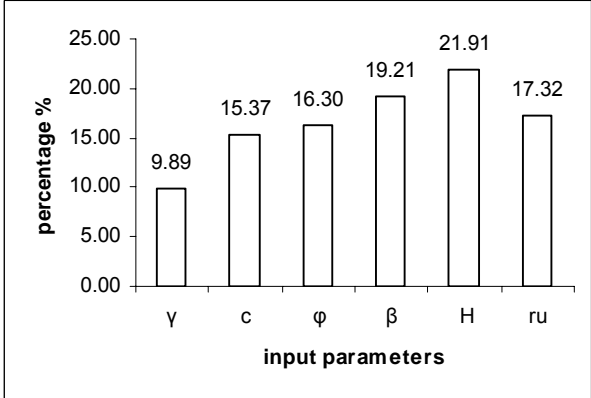


Figure 4: Relative importance of the parameters contributing to safety factor estimation (Ferentinou and Sakellariou 2007)

As shown in figure 3, among the 4 parameters used as input data in the training procedure, the parameters concerning the geometry of the tunnel (tunnel depth – z_0 and diameter – $2R$) are of a paramount importance, mainly affecting the tunnelling induced settlements. The excavation method and the geology seem to have less importance than the above mentioned ones, but they still possess a high percentage (19.08% and 13.30% respectively).

3.3 Conclusions

In this study, the Back Propagation algorithm was used so as to reveal the hierarchy and relevant importance of each of the parameters mainly affecting the total amount of the induced settlements due to tunnelling. The results from the application of the method of the partitioning of connection weights, has shown that the geometry of the tunnel is of a major importance but also the excavation method and the geology must always be taken into consideration. From the above mentioned and the experience gained from previous studies, Ferentinou (2004), Sakellariou and Ferentinou (2005) and Ferentinou and Sakellariou (2007), concerning the estimation of the stability of Soil and Rock Slopes, the application of computational intelligence tools on the real-world data sets using both supervised and unsupervised methods gives reasonable results which leads to the conclusion that the method is promising and should be further exploited.

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