

A QUICK TOOL FOR THE PREDICTION OF TUNNEL CROWN DISPLACEMENT USING NEURAL NETWORKS

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ABSTRACT

Artificial Neural Networks (ANN) and deep learning currently provide rigorous solutions to many engineering problems like in geotechnical engineering which can be used mostly in deformation prediction and back analysis. In this paper, deformation monitoring data from measured absolute displacements in a tunnel excavated at a complex geological system of the Pantokrator Limestone with fractured and loose cataclastic gouge using the New Austrian Tunneling Method has been used to train an ANN for prediction of the crown displacement along a tunnel. A Multi-layered Perceptron neural network has been developed and used as a quick tool for deformation behavior prediction (crown displacements) of the tunnel using the monitoring data measurements as target data and input training data from deformation parameters like the overload factor, the support class, the stress reduction factor, the rock mass category, the coefficient of lateral earth pressure and the overburden height. A detailed description of the developed ANN is given and results are shown which indicate the suitability of the proposed method.

1.0 INTRODUCTION

The need to upgrade and further develop transportation infrastructure (high-speed railway, highway and urban transit lines) has led to the ongoing construction of large-diameter, long tunnels under difficult conditions (Kavvas, 2003). In conventional tunneling, 'geotechnical monitoring' is of fundamental importance as an instrument of verifying the appropriateness of the operations specified in the design and for calibrating the intensity and sequence of those operations during construction. It is also important for recording tunnel behavior when it is in service, in order to check the condition of the tunnel over time, especially in relation to the geological behavior of the rock mass and possible changes in the hydrological conditions (fault zones, walled sections, inflow, etc.) (Lunardi & Gatti, 2010). Monitoring systems are designed to systematically acquire information on the geological-geomechanical conditions of a tunnel face and its deformation response during excavation and when in service.

The use of traditional manual data acquisition and processing methods in most cases have not been effective in preventing site failures due to the inherent real time limitations (Li et.al. 2008). On the other hand, due to modern day technology, advanced tunnel instrumentation and monitoring systems have been developed, providing digital instruments, centralized databases for monitoring data collection, automated real time updates and geo-spatial distribution of information. With the improvement in the amount and quality of data available to the tunnel engineers, the challenge remains at developing ways for its maximum utilization. This paper introduces the application of Artificial Intelligence Systems to develop a quick tool which can be used on-site for the prediction of tunnel crown settlement using Artificial Neural Networks (ANN) offering a simplified but essential way of utilizing big data available through the modern information systems.

2.0 IMPORTANCE OF DEFORMATION MONITORING IN TUNNELS

According to Kavvadas, (2003), monitoring of ground deformations in tunneling is a principal means for selecting the appropriate excavation and support methods among those fore seen in the design, for ensuring safety during tunnel construction (including personnel safety inside the tunnel and safety of structures located at ground surface) and finally, for ensuring construction quality management according to ISO9000.

In NATM tunnels, the observation method is usually applied, this is a tunnel construction method where continuous review of the behavior and update of the design and adjustment of construction method during construction, based on actual conditions and observations, as required is practiced. In this practice, the system behavior, the system stability and system accuracy are combined as design principles. During tunnel excavation, ground deformations are monitored and the measured values in the immediately previous excavation steps are used for the selection of the appropriate typical section to be used in the next excavation step, by matching predicted and observed deformations.

Ground deformation monitoring is extremely useful in tunneling projects (probably much more than in other geotechnical projects) for the following reasons:

Facilitation of the observation method: Ground deformations are the principal means of assessing tunnel behavior, therefore, ground deformation measurements are commonly used in the anticipation of ground response (and thus in decisions related to the applicable excavation and support methods).

Back analysis for better parameters: Deformation monitoring simplifies the process of assessment of ground parameters through back analysis of already excavated tunnel sections. The measurements around a tunnel are used as a criterion for acceptance of the ground parameters by matching the observed and predicted deformations.

Risk planning and Safety: Monitoring results are used in early warning systems during tunnel excavations, which promotes safety against incipient failures but also provides the ability for a timely intervention to save the structure but mostly to save the crew. The use of automated data collection methods can improve yet more on the speed and efficiency of risk mitigation systems in tunnel engineering.

Final lining design: Deformation monitoring also facilitates greatly in the design of the final lining of the tunnel. Lining design is governed by the loads exerted from the surrounding ground, which is obtained from stress and load measurements, but also clearly depicted in the deformation behavior of the tunnel during and after excavation.

Detection of surface movement: Ground monitoring is critically important in observation of ground surface settlement induced due to tunneling and as a control for mitigating excess movement of fragile structures near the tunnel.

Long term creep monitoring: Deformation monitoring can also be important in cases of excess creep development in a tunnel. Tunnel wall deformations can be used in assessing the condition of the rock mass around the tunnel and the evolution of the loads on the temporary support, although in some cases, conditions are so adverse that contingency measures do not succeed to avoid the eventual collapse, but the measurements can be used in redesigning the new approaches to re activate the tunnel.

2.1 TUNNEL DEFORMATION MEASUREMENTS

The ground deformation measurement methods applied during tunnel construction mainly depend on the nature of the tunnel in question. The methods applied in monitoring and design of urban/shallow tunnels are different from those applied in mountainous/deep tunnels. In mountain tunnels, the main objective of deformation measurements during construction is to ensure that ground pressures are adequately controlled, i.e., there exists an adequate margin of safety against collapse, including roof collapse, bottom heave, failure of the excavation face, yielding of the support system, etc.

Mountain tunnels: The adequate control of ground pressures is the basic objective of the engineer during construction in a mountain tunnel. Provision of a balanced support system to the internal pressures ensures a safe and economical structure, well adopted to the heterogeneity of ground conditions.

In mountain tunnels the ground deconfinement methods are applied before installation of supports and the final lining is installed later on after the stabilization of the tunnel creep deformations. Therefore, in this case the deformation monitoring measurements are;

- Concentrated inside the tunnel

- Emphasis is put on the accuracy of the convergence measurements
- Minimum surface monitoring is required
- High demand for efficient and timely measurement schedule
- The degree of precision may not be excessive as compared to the case of urban tunnels.

Urban tunnels: The construction and support methods applied in urban tunnels promote a stiff nature in the tunnel lining, so there is normally no convergence expected in the interior of the tunnel. Therefore, for deformation measurements in urban tunnels emphasis is put on close and precise measurements at the ground surface to ensure that neither there is uplift nor settlement above the tunnel. The characteristics of deformation measurements for urban tunnels include:

- Installation of monitoring devices long before excavation of a tunnel section.
- Very high precision is required
- Requirement of multi-system setting at different heights to capture any possible movement.
- Requirement of additional instrument set up around the tunnel environment and on other sensitive structures near the tunnel.

Despite the differences, every monitoring system needs to be sophisticated, systematic and able to provide a meaningful data to inform. Therefore, a master plan for deformation control should have such characteristics as:

- Thorough design of key parameters and influencing factors.
- Ability to monitor and record the key operation parameters in real time – advance rate, penetration rates, slurry pressures etc.
- Real time monitoring of effects on the surroundings – confinement, surface settlement, ground water flow etc.
- Compactness, durability, compatible with different types of sensors and monitoring software, and continuity in gathering data in real-time.

Deformation monitoring in tunneling projects is performed with instruments installed or operated either from the ground surface or from within the tunnel. Instruments installed from within the tunnel are necessarily put in place as the tunnel advances and thus an appreciable portion of the actual ground deformation is not recorded, as it has occurred prior to the installation of the instrument.

Typically, the majority of ground deformation takes place close to the tunnel face (from about one tunnel diameter ahead of the face up to about 1.5 diameters behind the face). Thus, monitoring instruments placed on the tunnel wall (e.g. optical reflector targets) or installed in the ground from the tunnel wall (e.g. borehole rod extensometers) should be installed as early as possible, (Kavvadas, 2003).

However, an exception to this unavoidable deficiency are ground deformations along the tunnel axis measured with sliding micrometers installed from the tunnel face, thus rendering extremely useful measurements for predictions of excavation conditions ahead of the tunnel face (these measurements are influenced mainly from the ground conditions ahead of the tunnel face and thus are useful in assessing tunnel behavior in the upcoming excavation stages).

The major deformation monitoring measurements usually performed in tunnel construction include:

- Measurements for wall convergence – instruments normally positioned inside the tunnel or drilled and installed inside the rock mass with the scope of monitoring wall convergence, crown settlement and face deformation.
- Measurements for in the ground – instruments placed vertically or horizontally in the rock mass to monitor general movement of the tunnel e.g. due to landslides, ground settlement or upheave.
- Measurement of deformation at the ground surface – mostly for urban and shallow tunnels for monitoring surface settlement and structural safety of buildings and utilities.

All the measured data is collected using advanced automated systems, stored in a central database and geospatially distributed for access by project personnel wherever they may be. Fig. 3.1 shows the architecture of an automated tunnel monitoring system.

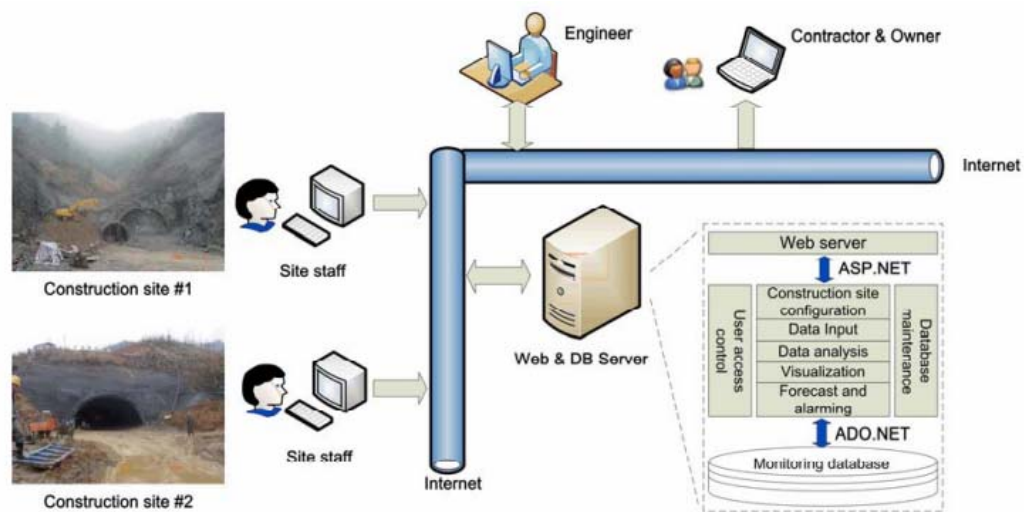


Figure 1: Architecture of an automated tunnel monitoring system, (Source: Li et. al. 2008)

2.0 NEURAL NETWORKS

Neural networks and deep learning currently provide the best solutions to many problems in image recognition, speech recognition, and natural language processing but also their application in geotechnical engineering is growing rapidly. They are the most commonly applied intelligent system in solving geotechnical engineering problems. For example, Bourmas, (2014) used a combination of ANN and generic algorithms to assess the factor of safety of column and chamber mine; Tsekouras, (2004) used ANN to predict tunnel behavior using FEM analysis results; You, (2013) used ANN in back analysis with face mapping data to assess the optimal geotechnical parameters to be used in FEM analyses.

2.1 ARTIFICIAL NEURAL NETWORKS (ANN)

ANN is a software implementation of the neuronal structure of the human brain. Though the biology of a human brain is so complex, it has been proved that it contains neurons which are kind of like organic switches. These can change their output state depending on the strength of their electrical or chemical input. A neural network is a hugely interconnected network of neurons where the output of any given neuron may be the input of thousands of other neurons (Basheer and Hajmeer, 2000, Hagan, 2012). Learning in the human brain occurs by repeatedly initiating certain neural connections over others and this reinforces those connections. This

makes them more likely to produce a desired output given a specified input. This learning involves a feedback i.e. when a desired outcome occurs, the neural connections causing that outcome become strengthened. The ANN is comprised of three sections;

- The input layer
- The hidden layers and
- The output layer

Each layer contains a number of neurons, where each neuron is connected to other neurons from the previous or the next layer through a weight. When each neuron receives an input signal (x_n), it multiplies it by the adjustable weight (w_n), sums all the incoming signals and a weighted bias product is added to the sum. This combined input (l_j) is then passed through an activation transfer function ($f(l_j)$) to produce the output element (y_j). The neuron outputs are transmitted to the output layer and then to the user's interface (Fig. 2). The network adjusts its weights on the presentation of an input data set and uses a learning rule to find a set of weights that will produce the input/output mapping with the smallest possible error, (Lee & Akutagawa, 2009).

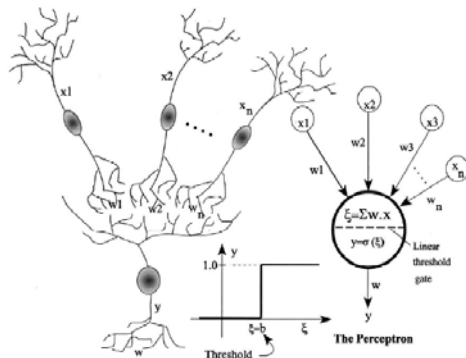


Figure 2: Relationship between biological and artificial neurons (source: Basheer et.al, 2001)

ANN have the major advantage that they can be trained and can learn using a series of input data from a related problem. When the training is successfully performed, it can then be validated using an independent data set. The ANN uses the provided data to adjust their weights in an attempt to capture the relationship between the model input variables and the corresponding outputs. A learning algorithm is chosen as a learning function for tuning the values which are to be taken by the weights and biases during the analysis.

This paper uses the Backpropagation Neural Networks (BPNN) which is popularly applied in classification and prediction problems.

2.2 THE ANN MODEL

The purpose of building a ANN model is to create a tool with which engineers can make quick predictions of the tunnel deformation during tunnel construction or even in design in case the training data is from an already excavated tunnel but with similar technical geological rock mass conditions.

In this paper, an Artificial Neural Network approach for predicting crown displacement of a tunnel using a set of training data based on indirect parameters from Peck, (1969); Kavvas, (2007) such as the overburden factor N_s , and the stress reduction factor λ , as inputs and field measured displacement as target data is performed. The factors mentioned above were presented through various parameters, namely:

1. The overload factor N_s which represents the load overburden p_o and the uniaxial compressive strength of the rock mass.

$$\text{The overload constant, } N_s = \frac{2p_o}{\sigma_{cm}}$$

2. The modulus of elasticity E , - this represents the stiffness and plastic behavior of the rock mass

3. The stress reduction factor λ , - this is the measure of the influence of the distance of the placement supports on a tunnel of radius R . (case where no plasticity occurs around the tunnel during excavation.

$$\lambda = 1 - 0.75 \left[\frac{1}{1 - \frac{3}{4} \left(\frac{x'}{R} \right)} \right]^2$$

4. The support classification as a rating of the pressure exerted by the support system on the tunnel walls to counter deformation.
5. The rock classification as an in-field classification for conditions as seen and judged by the engineer
6. The overburden load burden P_o
7. The coefficient of lateral pressure K_o around the tunnel environment

The inclusion of convergence-confinement parameters N_s and λ is to create a means of comparative use of both the finite element analysis and ANN.

3. CASE STUDY

The data used to train the ANN is S1 tunnel which is among the tunnels of Egnatia Highway and is found between the villages of Kristallopigi and Psilorahis in Hpeiro, 35km East of Igoumenitsa (Fig. 3).

Table 1: Factor and parameters that affect tunnel deformation.

Deformation factor	Tunnel parameters
Tunnel geometry	Depth, Diameter, Shape
Ground conditions	Cohesion GSI, E, ν, σ_{ci} Lateral earth pressures
Excavation conditions	Excavation step Number of sequences Face pressure (TBM)
Support conditions	Use of forepoles and /or spiles, Lining, bolts, Steel frames

During the construction of the S1 tunnel, uniquely difficult geological formations were encountered. It was a Pantokrator limestone rock mass of cataclastic type with high flow characteristics, heavily weathered and broken with interchanges from fully fragmented rock to complete gravel and clay materials. During the construction of the tunnel, it was discovered that the deformation behavior designed basing on the in-situ stress conditions and test drills was different from the one encountered. This implied that the analytical methods used in the design gave conservative support

solution because it didn't allow for the flow behavior of the material. Therefore, the observation method had to be emphasized, and it was proved that the basic solution for safe tunnel excavation was an aversive approach, to first of all hold and retain the loose material and later to provide the support system as per the analyses (Lefas et al., 2001).

For the construction of the neural network model, the data obtained from the article by Georgiannou et. al. (2007) as aforementioned was used as input data for the neural network model (Table 1). The technical-geological data including the rock mass class, the tunnel depth, the support class and consequent displacement for sections along the tunnels were retrieved from the 1170m tunnel length. In this case 117 data sets of seven parameters are obtained. Therefore, the total number of data elements available for the neural network is 819 elements and 117 target elements. The data is processed through a min-max normalization.



Figure 3: Location of the S1 tunnels of the Egnatia Highway, (Source: Google Earth).

3.1 Neural network architecture

Using the Matlab Neural Network Tool a series of network analyses are performed on a Multi-Layer Perceptron to select the optimum number of layers, the number of neurons in the hidden layer, the learning algorithm, and consequently the optimum training parameters (learning rate, momentum and validation rate).

Table 2: Optimum training parameters obtained from the test analysis set with the smallest MSE and highest R².

NETWORK FUNCTION	PARAMETER
TRANSFER FUNCTION	TANSIG
TRAINING ALGORITHM	BAYESIAN REGULATION
LEARNING ALGORITHM	LEARNGDM (gradient descent with momentum function)
VALIDATION CHECKS	1000
No OF HIDDEN LAYERS	1
No OF INPUT ELEMENTS	7
No OF NEURONS	7
LEARNING RATE/ MOMENTUM	0.1 /0.4
MAX PERFORMANCE RATE	1E+20
No OF OUTPUT LAYERS	1

The quality and accuracy of the prediction is given in terms of the Mean Square Error (MSE) and Regression (R²).

$$MSE = \frac{1}{N} \sum_{i=1}^N (Y_i - X_i)^2$$

$$R^2 = \frac{\sum_{i=1}^N (X_i - \bar{X}_i)(Y_i - \bar{Y}_i)}{\sqrt{\sum_{i=1}^N (X_i - \bar{X}_i)^2} \sqrt{\sum_{i=1}^N (Y_i - \bar{Y}_i)^2}}$$

Where X_i is the target value (field monitoring measurement), Y_i is the predicted value and N is number of input data pairs.

4. RESULTS

Learning: After successful training of the proposed ANN model, it was proved that it can perfectly learn with a good degree of regression and MSE as shown in tables 3 and 4. The predictive model performed well and confirmed that artificial neural networks can be successfully used for prediction of tunnel behavior in the study.

Table 3: Performance results of the final artificial neural network tool.

R2 TRAINING	R2 VALIDATION	R2 TESTING	MSE TRAINING	MSE VALIDATION	MSE TESTING
90,4%	96%	97.3%	24,7	30,68	34,67

Table 4: Root Mean Square Error of the training data in mm.

RMSE TRAINING	RMSE VALIDATION	RMSE TESTING
5mm	5.5mm	9mm

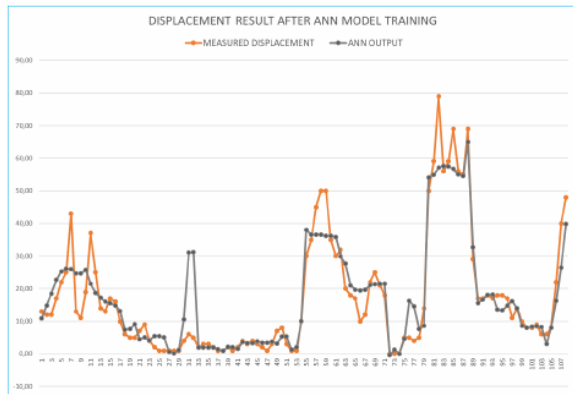


Figure 4: Fitting of the predicted learning displacements with the field measured crown displacements.

Prediction: The neural network model is established for the prediction of crown displacement at a position $x(m)$ behind the tunnel face. If during construction, based on previous geotechnical investigations, the engineers can gather enriched information on the geological and geotechnical characteristics of the tunnel environment, then by calculating and establishing the seven parameters used in training the artificial neural network, a good prediction of the displacement field can be obtained. The regression plots of the predicted data and the measured data give a satisfactory compliance with $R^2 = 0.87$. The results of the test are presented in Fig. 5 and 6.

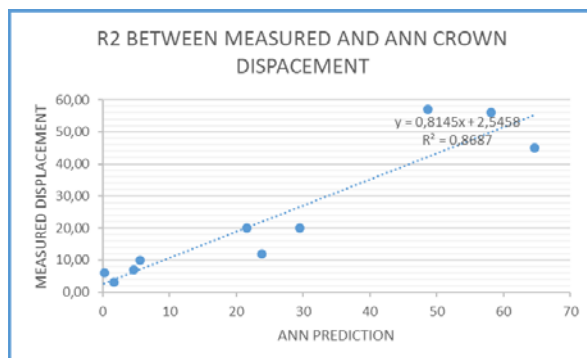


Figure 5: correlation between the ANN predicted displacements and the field measured crown displacement.

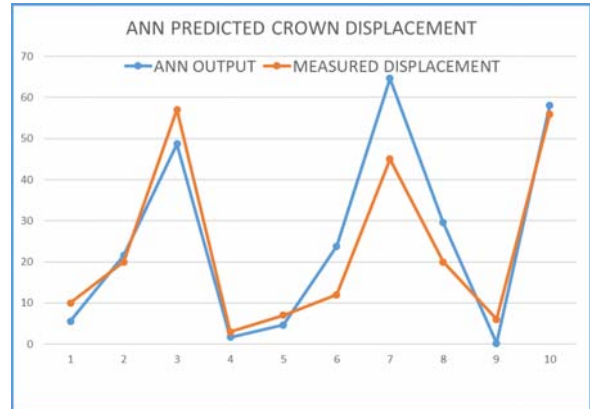


Figure 6 Fitting of the predicted and the field measurement crown displacements.

4.1 SENSITIVITY ANALYSIS OF THE ANN

The development of a deterministic or stochastic model which is based on little or missing data characterized by large error approaches, can lead to predictions which do not relate with the empirical evaluation or specialized knowledge (Johnson & Winchern, 2007). Therefore, the sensitivity of the neural network model should be examined/ checked to see the effects of input data variations on the training results. In the sensitivity checks, the interrelationship and the influence of the data elements are analyzed so as to identify the elements which have the highest influence on the results. Seven parametric analyses are performed by retraining the neural network, each analysis with one of the input element values zeroed. The performance results of the analyses are summarized in Table 5. The regression (training) of the target data with the trained data from the Rock class, K_o , Support class and λ are minimally affected while for the elastic modulus E , N_s and Overburden is reduced drastically.

Table 5: Performance results from the sensitivity analysis of neural network.

	ROCK CLASS	SUPPORT CLASS	E	K_o	N_s	OVER BURDEN	λ	ANN
$R_{testing}$ (%)	92,7	90,6	47	93	39,7	72,5	81,3	97,3
MSE	29,2	173	28,4	63,2	56,1	46,3	27	24,7
RMSE(mm)	5,5	13,1	5,2	7,9	7,5	6,8	5,1	4,9

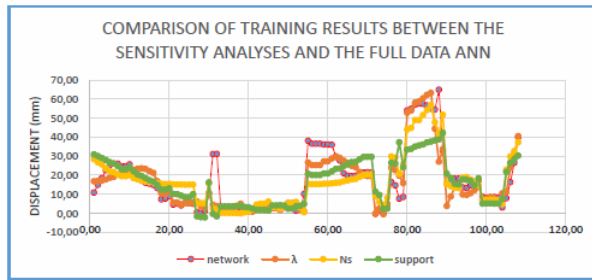


Figure 7: Comparison of training results for sensitivity due to reduction to zero of input data.

4.0 CONCLUSIONS

The multi-layer perceptron backpropagation network used for the prediction of tunnel crown displacement with ANN architecture comprised of a sigmoid transfer function and Bayesian Regularization learning algorithm, the architecture is 7-7-1, the learning rate 0.1 and momentum increment 0.4.

The network is trained in a Matlab neural network tool, with 108 input training sets and 10 test sets. The regression R² between the target (measured) displacement and the predicted displacement is 87%, the Mean Squared Error of 24.7 and the Root Mean Squared Error 4.9mm.

Consequently, the artificial neural network model created gave a truly reliable result leading to the conclusion that artificial neural networks can be used as a quick tool to predict tunnel behavior as a means of ensuring tunnel safety, real time data analysis and minimization of tunnel failure risks.

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