Geotechnical Aspects of Underground Construction in Soft Ground, Kusakabe, Fujita & Miyazaki (eds)
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Neural networks as a means for predicting convergence in tunnels

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ABSTRACT: Whereas a number of different analytical and numerical methods are presently available for calculating the size of rock deformations in the vicinity of a tunnel, the author's aim has been to develop a new method for the prediction of maximum (H1) convergence, based on neural networks. Two different types of neural networks, a back-propagation network and an LVQ network, were investigated. Based on 11 selected input parameters, a correctly learnt neural network was in both cases developed, which was able, in the great majority of cases (more than 80 %), to reliably predict maximum convergence during tunnel construction. Comparisons between the results obtained using this method (for 4 tunnels, with 292 typical cross-sections) and those obtained using a suitably selected mathematical model also showed that these two methods can be used, together, for the selection and detailed design of support systems for particular tunnel sections.

1 INTRODUCTION

The rock deformations which occur during the construction of tunnels are an important indicator of the stability of such structures, and of the adequacy of the support systems being used to build them. During construction, measurements are made of convergence. The geology and geomechanical properties of the rocks are monitored, as well as the presence of water, and measurements are made of the convergence of the tunnel's side walls. All the assembled data are used as a basis for adjusting the support structure as excavation works proceed, taking into account the conditions in the tunnel. The New Austrian Tunnel Method (NATM), which has been used for all tunnel construction in Slovenia over the last 10 years, allows for adjustments to be made in the support structure during the construction process, taking into account observed rock geology and measured convergence.

The purpose of the research described in this paper has been to determine whether it is possible to use neural networks for predicting tunnel convergence. The basis upon which such predictions can be made consists of the data obtained by geologists during preliminary investigations, as well as from the tunnel face during construction.

Numerical and analytical methods for calculating deformations in the vicinity of the tunnel require accurate geomechanical data about the rock, e.g. its elastic modulus, friction angle, and cohesive strength. In the case of very heterogeneous rocks, these items of data are very hard to determine with sufficient accuracy. A learnt neural network should, together with numerical and analytical methods, contribute towards the more accurate prediction of rock deformations occurring in the vicinity of the excavated tunnel.

When preparing the data base for the investigation described in this paper, data from all tunnels which have been built in Slovenia over the last 10 years were used. The rocks in these tunnels have, in general, been very heterogeneous and frequently tectonically deformed. The tunnels were of the single tube type, data from tunnels with two tubes being used only when the results of measurements indicated that the construction of one tube had no influence on the other. In total, almost three hundred cross-sections were analyzed. If, as occurred in some cases, convergence had not been measured at the selected cross-section, then it was interpolated from values observed at neighboring cross-sections with practically the same rock composition.

2 EXPERIMENTAL PROCEDURE

2.1 *Description of the structure of the neural networks*

When performing calculations using neural networks, two algorithms were used: Back-Propagation and Learning Vector Quantization.

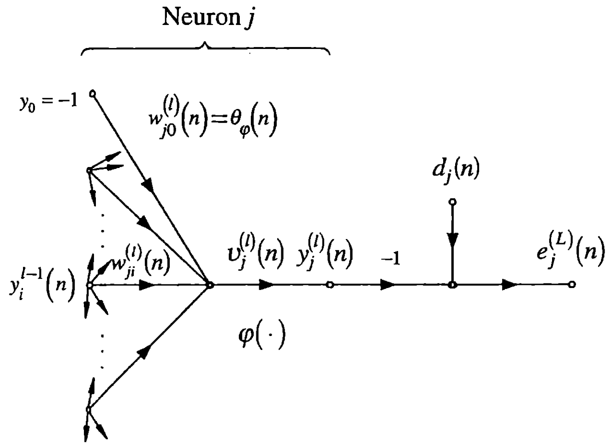

Figure 1. Signal flow in a back-propagation network

2.1.1 *Back-propagation network*

The back-propagation network consists of an input line, one or more hidden lines, and an output line. The back-propagation algorithm is repeated until the difference between the desired and the computed result converges to a minimum. The neurons are connected together by means of synaptic weights.

The following training data are assumed:

$$\{[x(n), d(n)]; n = 1,2,\ldots N\} \tag{1}$$

Back-propagation learning takes place as follows:

(a) initialization of the synaptic weights
Learning is begun with small values for the synaptic weights $\boldsymbol{w}$ and for the threshold levels θ.

(b) presentation of training examples
Examples are presented to the network in epochs, with forward and then backward computation.

(c) forward computation
Let the training examples in the epochs be given by $[\boldsymbol{x}(n), \boldsymbol{d}(n)]$, where $\boldsymbol{x}(n)$ is the input vector, and $\boldsymbol{d}(n)$ is the desired vector. The signals within the network are computed by iteration, from the network's input to its output. The internal activity for neuron j and layer l is calculated from the expression:

$$v_j^{(l)}(n) = \sum_{i=0}^{p} w_{ji}^{(l)}(n) y_i^{l-1}(n) \tag{2}$$

where $y^{(l-1)}(n)$ is the function signal of neuron i connected to the previous layer l–1 after iteration n. The synaptic weight $w_{ij}^{(l)}$ connects together the signal from neuron i, which lies in the previous layer l–1, and neuron j in layer l.

When using a sigmoid function as an activational function, the output of neuron j, in layer l, is calculated from the expression:

$$y_j^{(l)}(n) = \frac{1}{1 + e^{-v_j^{(l)}(n)}} \tag{3}$$

If neuron j is in the first hidden layer $l = 1$ then:

$$y_j^0(n) = x_j(n) \tag{4}$$

where $x_j(n)$ is the j^{th} element of the input vector $\boldsymbol{x}(n)$. If, however, after iteration n neuron j is in the output layer $j = L$, then:

$$y_j^L(n) = o_j(n) \tag{5}$$

The signal of the error is calculated from the following expression:

$$e_j(n) = d_j(n) - o_j(n) \tag{6}$$

where $d_j(n)$ is the j^{th} element of the desired expected vector $\boldsymbol{d}(n)$.

(d) backward computation
The local gradient is calculated by backward iteration from layer to layer in the direction from the output towards the input. For neuron j in the output layer L:

$$\delta_j(n) = e_j^{(L)}(n) o_j(n)[1 - o_j(n)] \tag{7}$$

and for neuron j in the hidden layer l:

$$\delta_j^{(l)}(n) = y_j^{(l)}(n)[1 - y_j^{(l)}(n)] \sum_k \delta_k^{l+1}(n) w_{kj}^{(l+1)}(n) \tag{8}$$

The synaptic weight for layer l is learnt according to the generalized delta-rule:

$$w_{ji}^{l}(n+1) = w_{ji}^{l}(n) + \alpha[w_{ji}^{l}(n) - w_{ji}^{l}(n-1)] + \eta \delta_j^{(l)}(n) y_i^{l-1}(n) \tag{9}$$

where η is the learning factor and α is the moment.

(e) iteration
With the use of new epochs, iterations are performed until the average squared error converges to a minimum value, i.e. zero. The training examples are presented to the network randomly. As the number of iterations is increased, the learning factor and the moment are reduced.

2.1.2 *Learning Vector Quantization (LVQ)network*

The LVQ network consists of the input layer, a Kohonen layer, and an output layer. In the Kohonen layer the learning of this network takes place.

It is a characteristic of the learning process that it defines the input vector into classes of the input space. A reproduction vector is defined for each class. The assembly of possible reconstruction vectors is known as the reproduction code-book. The vector with minimum distortion is known as the Voronoi vector.

Let us take as an example a randomly selected vector of the input space. If the classification of the input vector and of the Voronoi vector $\boldsymbol{w}$ agree, then

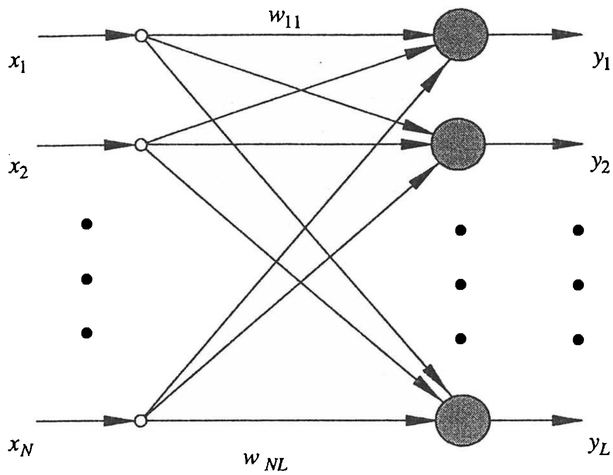

Figure 2. Signal flow in a LVQ network

the vector $\boldsymbol{w}$ shifts towards the input vector $\boldsymbol{x}$. If, however, these two vectors do not agree, the Voronoi vector $\boldsymbol{w}$ will shift away from the input vector $\boldsymbol{x}$.

Calculations using the LVQ network take place according to the following steps:

(a) initialization of the Voronoi vectors

Let $\{w_j \mid j=1, 2,..,N\}$ be a group of Voronoi vectors, and $\{x_i \mid i=1, 2,..,L\}$ a group of input vectors. Let us assume that there are many more input vectors than Voronoi vectors, and that the Voronoi vector $\boldsymbol{w}_c$ is the vector which is closest to the input vector $\boldsymbol{x}_i$.

(b) learning

Let $\mathcal{C}_{w_c}$ be a class defined by the Voronoi vector $\boldsymbol{w}_c$, and let $\mathcal{C}_{x_i}$ designate the class of the input vector $\boldsymbol{x}_i$. The Voronoi vector $\boldsymbol{w}_c$ then learns in the following way:

If $\mathcal{C}_{w_c} = \mathcal{C}_{x_i}$ then

$$w_c(n+1) = w_c(n) + \alpha_n\left[x_i - w_c(n)\right] \tag{10}$$

where the learning factor lies between the limits $0<\alpha_n<1$.

In this case the winning neuron is in the correct class. If, on the other hand, $\mathcal{C}_{w_c} \neq \mathcal{C}_{x_i}$, then

$$w_c(n+1) = w_c(n) - \alpha_n\left[x_i - w_c(n)\right] \tag{11}$$

In this case the winning neuron is not in the right class.

In all other cases the Voronoi vectors do not change. It is desirable that the learning factor α_n is gradually reduced as the number of iterations n is increased. After several transitions through the input data, the Voronoi vector will converge and the learning process will be complete.

(c) stopping rule

It often occurs that the network overlearns. When the optimum accuracy of prediction has been achieved, and if the iteration is continued, the accuracy of the results obtained by the calculations will be reduced. The best way to determine the optimum number of learning steps is multiple testing.

2.2 *Input and output data*

Data for the neural network analysis were selected, for each investigated tunnel, from the latter's cross-sections. For each cross-section those parameters were chosen which have an important effect on convergence. The majority of the data for the selected parameters were determined on the basis of an engineering-geological description of the rocks at the tunnel face. The method of tunnel support is described using the categories defined in the NATM tunnel construction method.

The order of magnitude of maximum convergence was selected as the output item of data from the learning process which interested us the most. The maximum convergence at the selected cross-sections were taken into account.

Only those tunnel cross-sections which had a sufficient number of reliable data were selected for analysis. Cross-sections where additional strengthening works had to be carried out, or where the data were incomplete, were not considered.

Due to the influence, on the development of convergence, of the depth of the tunnel below ground surface, and of the size of the in situ stresses in the rock, a distinction was made, in the learning process, between deep tunnels having an overburden of over 150 m, and other tunnels having lesser overburdens.

In the early stages of the research, attempts were made to include as many observed data as possible. Thus, initially 21 parameters were taken into account, but the calculations produced poor results. By making numerous calculations it was proved that the optimum number of parameters for any given cross-section was 11.

The following input parameters were selected:

- the height of the overburden
- the type of the rock, which makes up the majority of the given cross-section (see Table 1)

Table 1. Rock type class as an input parameter for the network.

Class.	Description
1	clay
2	claystone, siltstone
3	marl
4	sandstone, limestone, dolomite

- the rock quality designation (RQD) of the rock at the selected cross-section
- the type of the rock which, at the given cross-section, appears to a lesser extent
- the RQD of the rock which, at the given cross-section, appears to a lesser extent
- the occurrence of a tectonic zone (see Table 2)
- the stratification of the strata and cracks with respect to the direction of construction of the tunnel (classification according to Bieniawski)
- the type of cracks (classification according to Bieniawski)
- the number of larger faults
- the support system type (categories according to the NATM method)
- the occurrence of water in the tunnel (classification according to Bieniawski)

The wanted output item of data was the size of the "maximum convergence H1", which was defined by the relative movement of two fixed measuring points on the left-hand and right-hand side walls of the excavated gallery of the tunnel. Taking into account the actual measured size of the convergence, two classification types were selected, which are represented by two neurons in the output lines of the neural network.

2.2.1 *Tunnels having depths below surface of less than 150 m*

When predicting the convergence of tunnels having depths below surface of less than 150 m, the measured convergence was classified into two classes. In the first class convergence did not exceed 5 mm, whereas in the second class it exceeded 5 mm.

From among all the investigated cross-sections, 184 were selected for calculations of convergence. These cross-sections were selected in such a way that different types of rock were included, and of all these 104 cross-sections were selected for learning purposes. The other cross-sections were used for testing purposes.

In the next step the input and output layers contained only one neuron. In this way it was possible to predict not only the convergence class but also the actual size of the maximum convergence H1. For the prediction of results the back-propagation network is the most suitable. The LVQ network can only be used when looking for solutions to classification problems.

Table 2. Tectonic zone class as an input parameter for the network.

Class.	Description
1	occurrence of a tectonic zone
0	the rock does not lie in a tectonic zone

2.2.2 *Tunnels having depths below surface of greater than 150 m*

Among all the investigated tunnels in Slovenia, the Karavanke Tunnel, completed in 1991, assumes a special place. With an average depth of approximately 1000 m, the in situ state of stress of the rocks in the direct vicinity of the tunnel was relatively high. During construction, convergence were measured of up to 1600 mm, so it was decided that the data corresponding to this tunnel should form a separate group of data belonging to tunnels having depths below surface of greater than 150 m. The cross-sections in the tunnel were divided into two groups: the first group consisted of cross-sections where the measured H1 convergence amounted to 150 mm or less, whereas the second group included those cross-sections where this convergence exceeded 150 mm.

From a total of 108 investigated cross-sections, 59 were used for the learning process, and 49 were used for testing purposes. In the next step the actual size of the maximal convergence $H1$ was predicted by means of neural networks.

3 RESULTS

The back-propagation network, which was used in calculation, gave satisfactory results, consisted of two hidden layers. The first layer consisted of 8 neurons, and the second of 6 neurons. In the case of the LVQ network, the Kohonen layer consisted of 50 neurons.

3.1 *Tunnels having depths below surface of less than 150 m*

The final calculations using the back-propagation network showed that this network had learned correctly how to classify the input signals into two classes. At the testing stage, the learned neural network correctly classified all 30 input examples.

At the next stage, when the neural network was used to predict convergence, among the 30 items of test data, a correlation, between calculated and desired data, of 0.93 was, achieved.

Calculations using the LVQ network, too, correctly classified all of the test data with correlation of 0.92.

3.2 *Tunnels having depths below surface of greater than 150 m*

During the testing stage of the back-propagation network, in the case of tunnels with overburdens greater than 150 m, 4 items of data were incorrectly classified.

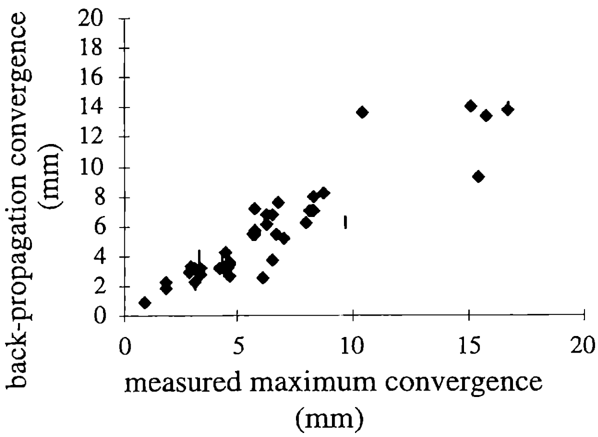

Figure 3. Measured maximum convergence plotted against the convergence predicted by the back-propagation network, for tunnels having depths below surface of less than 150 m

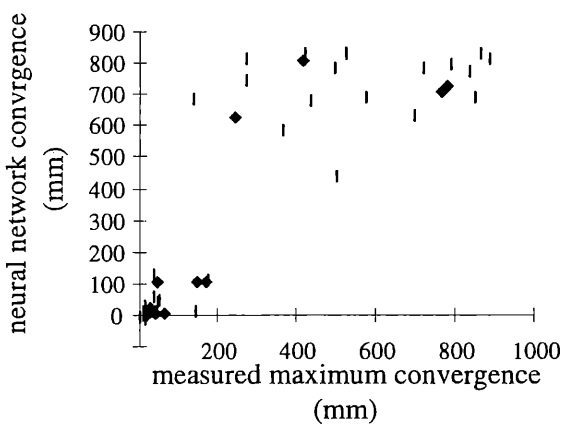

Figure 4. Measured maximum convergence plotted against the convergence predicted by the back-propagation network, for tunnels having depths below surface of greater than 150 m

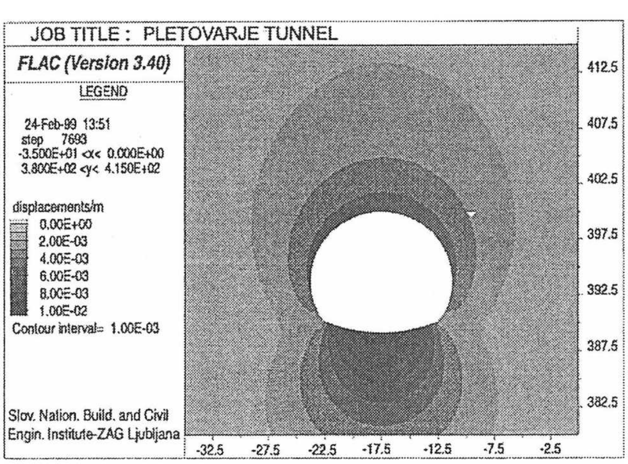

Figure 5. Rock deformations in the vicinity of the finally excavated cross-section P5 of the Pletovarje Tunnel (South Tube)

On the basis of the test data, it can be stated that in 88 % of all cases this network was able to make a correct prediction of the convergence in tunnels with high overburdens.

When predicting the actual size of the convergence, the back-propagation network was successful in predicting with an correlation 0.86 between the input and the output signals of the network. A greater scatter of results can be observed in the case of convergence between 200 and 500 mm. High values of measured convergence mostly occurred in the perm-carbonic shale. This is because when the rock deforms beyond the plastic yield point, it is difficult to make a correct prediction of the deformations which will occur in the direct vicinity of the tunnel.

3.3 *Comparison of the results obtained using neural networks with those obtained using a numerical model*

Neural networks, together with numerical modeling, contribute to the optimization of the choice of support system. In the first step of calculations using the method with the learnt neural network, a prediction is made of the deformations which will occur during excavation of the tunnel. In the next step, by back-analyses numerical modeling, excavation of the tunnel is simulated. From calculations of the numerical modeling of the support system, it is then possible to estimate whether the latter is too stiff or too weak, taking into account the calculated deformation in the vicinity of the rock.

In Figure 5 are presented, as an example, the calculated deformations for cross-section P5 of the Pletovarje Tunnel (South Tube), at 29+908m on the Hoce - Levec section of the Šentilj - Gorica motorway. This tunnel was constructed in mixed sandstone, marl, mudstone and claystone. At the treated cross-section, the rock consisted mainly of dark gray and black foliated marl. The RQD of the marl was estimated as 0. The selected cross-section lies in a tectonically deformed zone, and two significant cracks were mapped running across the whole cross-section. There was, however, no water at the selected cross-section.

The cross-section is supported by Category 5 support system. For the calculations of maximal convergence with learnt neural networks, the selected cross-section was described by means of the following input vector $\{x_1, x_2, ..., x_{11}\}$:

$$\{28,3,0,3,0,1,5,5,2,5,1\} \quad (12)$$

The neural network allocated the selected cross section of the tunnel, of the class having a convergence greater than 5 mm. The predicted convergence was 7.2 mm.

By means of backwards analysis using a numerical model, the following geomechanical characteristics of the rock were obtained:

- γ specific mass 2600 KN/m^3
- φ friction angle 26°
- c cohesive strength 0.2 MPa
- E elastic modulus 670 MPa
- σ_H/σ_V in situ state of stress: 1.0
- T tensile strength 0.0 MPa

The calculated maximum H1 convergence at the side walls of the tunnel at the measurement location was 8 mm. The maximum H1 convergence, measured at this cross-section using a convergence tape extensometer, was 8.2 mm. In the roof of the tunnel the calculated settlement amounted to 4.9 mm. Measurements showed that the crown of the tunnel had in fact settled, at this cross-section, by 6 mm (Petkovšek, 1996). The calculated stresses in the shotconcrete were, at the largest, 11 MPa. Relatively very small forces, amounting to between 10 in 61 KN, were measured in the measuring anchors, which agrees with the results of numerical calculations. It can be concluded that the supporting system had been designed optimally for this location in the tunnel. been designed optimally for this tunnel .

4 CONCLUSIONS

On the basis of the calculations performed using the back-propagation network and the LVQ network it can be concluded that both of these networks are suitable for predicting the maximum H1 convergence in tunnels. The selected input parameters are also sufficiently accurate to make it possible to predict convergence with a satisfactory degree of accuracy.

The type of rock and necessary support structures are sufficiently accurately described by the 11 selected parameters. The use of neural networks makes it possible to take into account, when calculating the size of the maximum convergence, many more parameters regarding rock quality than would be possible in the case of other methods.

The rock deformations which occur in the vicinity of tunnels can be satisfactorily predicted or, at least correctly classified, by means of the investigated neural networks. Together with suitable mathematical models, neural networks can also, by means of back analysis, be used to optimize the choice and design of support systems.

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