CETRA 2014

3rd International Conference on Road and Rail Infrastructure

28–30 April 2014, Split, Croatia

Road and Rail Infrastructure III

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Organizer
University of Zagreb
Faculty of Civil Engineering
Department of Transportation

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APPLICATION OF NEURAL NETWORKS IN ANALYZING OF ROCK MASS PARAMETERS IN TUNNELLING

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Abstract

One of the key problems in tunnelling is to define realistic parameters for rock mass properties as a basis for successful numerical modelling. The main goal of this problem is how to extrapolate the parameter from the zone of testing to the whole area (volume) that is of interest for interaction analyses of the system rock mass-structure. So it is necessary to find an appropriate way to find intelligent tools to combine data from empirical classification rock mass methods having in mind that there are a lot of variations in statistic values.
First step in the procedure is to divide the tunnel length in quasi-homogenous zones, while the second is to define adequate geotechnical and numerical models as a basis for interaction of rock – structures system and stress-strain behaviour of rock massif. Artificial neural networks (ANN) have been found to be powerful and versatile computational tools for many different problems in civil engineering over the past 2 decades. They have proved useful for solving certain types of problems, which are too complex, or too resource-intensive nonlinear problems to tackle using more traditional computational methods, such as the finite element method. ANN-s are intelligent tools, which have gained strong popularity in a large array of engineering applications such as pattern recognition, function approximation, optimization, forecasting, data retrieval, automatic control or classification, where conventional analytical methods are difficult to pursue, or show inferior performance. A review of some problems in tunnelling that were successfully solved by using neural networks is presented in this paper. A general introduction to neural networks (NN), their basic features and learning methods is given. After that, it is possible to use neural networks to solve necessary problems in tunnelling.

Keywords: tunnelling, rock complexes, classification, extrapolation, neural networks

1 Introduction

Neural Networks have made a remarkable contribution to the advancement of various fields of endeavor and have become very popular for data analysis over the past 2 decades. Their application in the civil engineering field is considered in this paper. Neural networks are intelligent systems that are based on simplified computing models of the biological structure of the human brain, whereas the systems based on traditional computer logic require comprehensive programming in order to perform a given task. Artificial Neural Networks (ANN-s) are suitable for multivariable applications where they can easily identify interactions and patterns between inputs and outputs. ANN models do not require complicated and time consuming finite element input file preparation for routine design applications. They are able to infer important information for the task, which is being solved by them, if data that is representative of the underlying process to be implemented, is provided. Neural networks have a self-learning ability, which is particularly useful where comprehensive models that are required for conventional computing methods are either too large or too complex to represent accurately, or simply doesn't exist at all.

2 Artificial Neural Networks – general overview

The functioning and the survival of intelligent systems depends on their system for processing information. The nervous system is the system for processing information in biological systems. It consists of the brain, as the central processing system for processing information and a set of sensors. The basic information element in biological systems is the neuron or the neural cell. There are billions of such processors in the brain. They are distributed, work simultaneously and cooperate. The neuron processors make the microstructure, the material basis of the biological intelligence. An approach to research of artificial intelligence is motivated by this observation and deals with the concepts of artificial neuron and artificial neural network, as the microstructure of artificial (synthetic) intelligence. Artificial neurons are inventions that are inspired by the anatomy and physiology of biological neurons. Figure 1 presents the morphology of a human neuron. It is assumed that the neuron is of an electrical nature – it has an electrical potential in respect to the environment. This electrical potential is changed due to external influences. The neuron has several inputs through which it receives electrical impulses, and only one output through which it sends an electrical impulse in the environment.

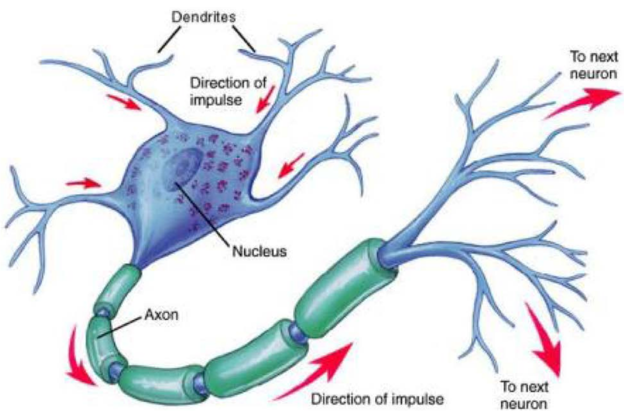

Figure 1 Example of a neuron morphology

Modeling of a neuron can be a very complex task. It involves the following key notions:
- body of the neuron (soma);
- axon – output neural strand through which it sends signals to other neurons;
- dendrites – growths of the soma which form a dendritic canopy;
- synapses – places in dendrites or soma where the neuron receives signals from other neurons; synapses are connections with other neurons;
- cumulative postsynaptic potential (SPP) is a cell potential, which is formed due to the cumulative synergistic influence of synaptic potentials;
- synaptic influence (weight): synapses have different influence on the formation of SPP. Some of them have a positive influence (excitation), while some have a negative effect (inhibition). Every synapse has its “weight” in the formation of SPP;
- threshold of the neuron excitation: minimal SPP needed for the triggering of an output signal from the neuron;
- presynaptic processing: processing of the biosygnals by direct connection of the axon with the synapses, before the potential is transmitted to the soma of the neuron;
- neural network: the structure of the connected neurons.

3 Artificial Neural Networks – general overview

Software NeuralTools ver. 6 provides a tabular view of all data analysis. Initially, it is necessary to define the variables and cases in which you need to model the problem. The values of variables are grouped in columns and name of them are written in the first row of the table. Each cases is represented by a series of table and is composed of a group of independent variables and known (or unknown) value of the dependent variable output . The goal is to predict the values of output variables for the cases for which they are unknown. To solve the given assignment problem, all data were grouped into two separate tables: the data for training and testing the neuronal network and data to predict the value of the output variable. Adopted the following independent variables:

- Bulk density (volume weight) γ;
- Compressive strength σ_p;
- Ingress of water;
- RQD – Rock Quality Designation;
- Average distance between leak (crack) Ls;
- Seismic velocity Vp.

Neuronal network has one output variable whose value depends on the input variables:

- RMR – Rock Mass Rating.

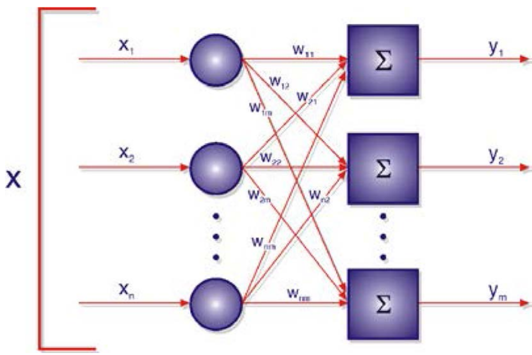

Figure 2 Model onelayer artificial neural network

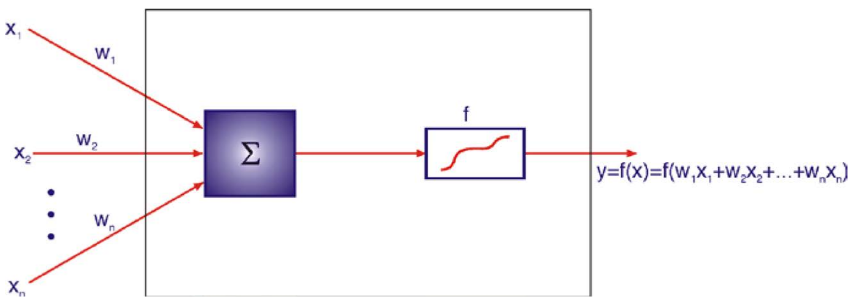

Figure 3 The neuron activation function

To solve the given problem were analysed 97 cases, of which 78 (80%) belong to the group of cases for training and the rest were used for testing the network.

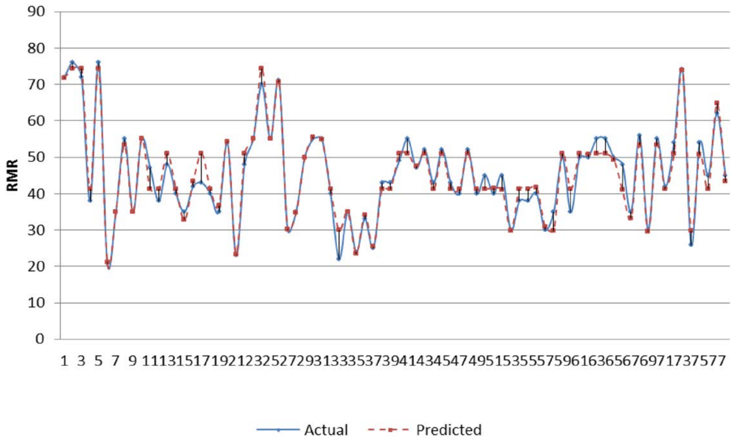

Figure 4 Cases of training

It may be noted that the trained neural network predicts a good quality rock masses RMR for inputs belonging to the interval sizes with which it was trained, or training for the 78 cases analyzed. The following figure shows a histogram of actual and predicted values for training cases and the frequency of their recurrence. Most of the residual values are around 0 which is a good indicator of the accuracy of the model for predicting RMR.

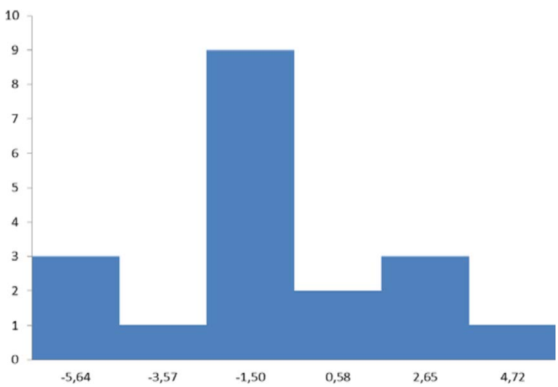

Figure 5 Histogram of residual values of training cases

Table 1 Residual values for test cases and their frequency of repetition

Residual value	Frequency of repetition
-7,030006814	3
-5,165334925	1
-3,300663036	9
-1,435991147	16
0,428680742	26
2,293352631	14
4,15802452	6
6,022696409	3
	Σ = 78

Neuronal network testing was performed on 19 data set that were not involved in the training of the network. Comparison of predicted RMR values obtained using the trained neural network and the expected results of the analyzed test cases is presented in follows figure.

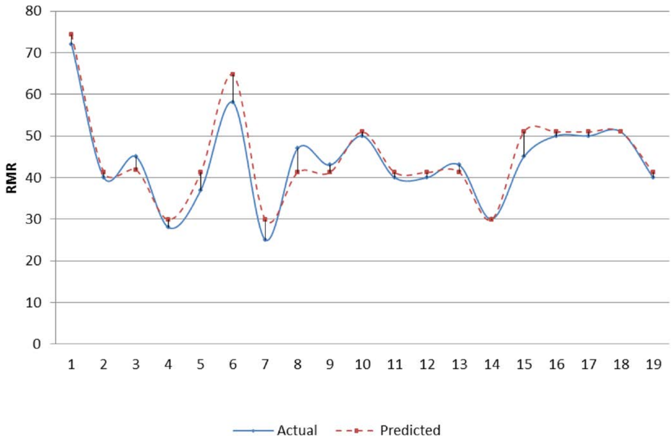

Figure 6 Graphic review of actual and predicted values for RMR test cases

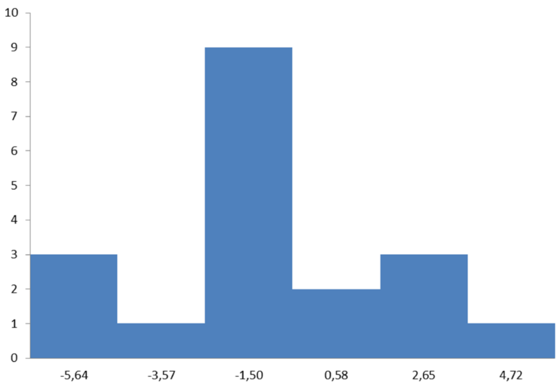

Figure 7 Histogram of residual values of testing cases

Testing the trained neural network confirms the fact that the model allows qualitative forecasting RMR on one side of the input data that were not used in the training of the network, for 19 cases of testing.

Table 2 Residual values for test cases and their frequency of repetition

Residual value	Frequency of repetition
-5,6423958	3
-3,5696133	1
-1,4968307	9
0,5759518	2
2,6487343	3
4,7215168	1
	Σ = 19

4 Conclusion

Although the first information about neural networks dates back to 1940, their practical application begun only four decades later, after discovery of appropriate algorithms which significantly increased their applicability. A lot of research is currently conducted in the sphere of neural networks, and these networks are increasingly studied at many universities all over the world. Neural networks are an example of a sophisticated modeling technique, and they have found their practical application in different areas, namely as a method for solving a variety of difficult and complex engineering problems. The application of neural networks for prognostic modeling aimed at predicting Rock Mass Rating – RMR is highly significant for the construction design process. Most experimental models are extremely expensive, while analytical models are quite complicated and time consuming. That is why a modern type of analysis, such as modeling based on neural networks, can be considered as extremely helpful, especially in cases when some prior analyses had already been made.

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