Prediction of Tunnelling-Induced Surface Settlement with Artificial Neural Networks, Case Study: Mashhad Subway Tunnel

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Abstract

In urban areas, it is essential to protect the existing adjacent structures and underground facilities from the damage due to tunneling. In order to minimize the risk, a tunnel engineer needs to be able to make reliable prediction of ground deformations induced by tunneling. Numerous investigations have been conducted in recent years to predict the settlement associated with tunneling; the selection of appropriate method depends on the complexity of the problems. This research intends to develop a method based on Artificial Neural Network (ANN) for the prediction of tunnelling-induced surface settlement. Surface settlements above a tunnel due to tunnel construction are predicted with the help of input variables that have direct physical significance. The data used in running the network models have been obtained from line 2 of Mashhad subway tunnel project. In order to

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predict the tunnelling-induced surface settlement, a Multi-Layer Perceptron (MLP) analysis is used. A three-layer, feed-forward, back-propagation neural network, with a topology of 7-24-1 was found to be optimum. For optimum ANN architecture, the correlation factor and the minimum of Mean Squared Error are 0.963 and 2.41E-04, respectively. The results showed that an appropriately trained neural network could reliably predict tunnelling-induced surface settlement.

Keywords: Surface Settlement, Artificial Neural Network, Mashhad Subway Tunnel, Prediction of Settlement.

Introduction

Complex underground constructions within the limited land of urban areas may cause serious damage to existing buildings, structures, and utilities. The estimation of the potential ground movements is needed to evaluate the stability of adjacent buildings and other facilities due to new tunnelling constructions.

To assess the damage of ground structures and negative effects of environment which is caused by ground settlement and deformation during tunnelling, large quantities of studies are presented by some scholars. Several approaches are used to predict the ground surface movement, such as empirical equation method, analytical solution method, numerical simulation method, and model test method (Zhiguo et al, 2011).

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Based on the numerous measured data of ground settlement during tunnelling and excavation, the concept of ground loss and the technique for estimating the ground settlement were proposed by Peck, (1969), who considered that the volume of surface settling tank was equal to the volume of ground loss under the condition of not to be drained. By analyzing the amount of tunnels which were constructed in clays, Attewell and Farmer (1974), found that it was effective to describe the longitudinal settlement curve using accumulative probability curve. Since the measured data are limited, the Peck's empirical formula cannot provide accurate prediction of all types of medium. Since all of these existing empirical formulas are based on the engineering practices, their precision is greatly influenced by the variety of geological conditions (Peck, 1969).

Analytical solution method is widely used in practice to predict the ground surface settlement by some researchers. For instance, based on the image method proposed by Sagaseta (1987), Verruijt and Booker (1996), the theoretical formula of vertical displacement, and horizontal displacement for soils were derived according to the assumptions that the soils were linear elastic materials. By using non-equivalent oval moving pattern of soil, and employing the equivalent ground loss parameter, Lee and Rowe (1992), Loganathan and Poulos (1998) modified the Verruijt and Booker's solutions of short term formula, and obtained the expression of vertical displacement. According to the upper bound theorems of plasticity, a new analytical method is

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introduced for calculating displacements during tunnelling, which is validated by five centrifuge tests on plane strain unlined tunnels in kaolin. Although some attempts have been made to obtain the closed form of analytical solutions for ground surface settlement, these methods are subjected to limitations. For instance, the formulas derived by Verruijt and Booker (1996), Loganathan and Poulos (1998), are based on the assumption that the soils are linear elastic materials. However, numerous experiments had demonstrated that the strength envelopes of geomaterials were nonlinear, and the linear relationship was just a special case. Consequently, the prediction results using analytical methods are generally different from the observed values (Yang and Wang, 2011).

In contrast to the analytical solutions, numerical methods make it possible to account for a group of factors describing the "soil-mass/tunnel" system, including the mutual effect of several tunnels. The combination of these methods and data derived from field observations will permit a more comprehensive investigation of the mechanism responsible for surface settlement, verification of various factors, and prediction of process development. Numerical methods have flexibility when applied, can simulate environment similar to the actual case, and can analyze effects on existing buildings. However, numerical methods are very complex and difficult to find a suitable soil model (Strokova, 2010).

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Model test method is a method that has simulated the tunnelling sequence, and is to observe the behavior of ground movement and collapse. At present, there is a favor to use centrifuge test which it can simulate actual force on the tunnel, proposed by Nomoto et al (1999). Laboratory experiments are an only way to study the actual mechanism of ground movement and collapse, but difficult to simulate real environment, and have effect of size sensitivity.

Over the last few years, Artificial Neural Networks (ANN) have been used successfully for modeling almost all aspects of geotechnical engineering problems. The literature reveals that ANNs have been extensively used for predicting axial and lateral load capacities in the compression and uplift of pile foundations (Shahin, 2008; Das and Basudhar, 2006), dams (Barkhordari Bafghi and Entezari Zarch, 2015; Behnia et al, 2013), liquefaction during earthquakes (Hanna and Saygili, 2007; Javadi et al, 2006), tunnels and underground openings (Mahdevari and Torabi, 2012; Gholamnejad and Tayarani, 2010; Yoo and Kim, 2007).

In this article, with respect to the successful modeling of geotechnical engineering problems with ANN method, measurements of settlement and ground movements recorded in line 2 of Mashhad subway tunnel project have been reviewed and analyzed. The data from this case study were used to train and test the developed neural network model to enable prediction of the magnitude of settlements

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and ground movements with the help of input variables that have direct physical significance.

Overview of Artificial Neural Networks

Artificial neural networks are a form of artificial intelligence, which by means of their architecture, try to simulate the behavior of the human brain and nervous system. They have the ability to relate input data and corresponding output data, which can be defined depending on single or multiple parameters for solving linear or nonlinear problems. Artificial neural networks do not require any prior knowledge or a physical model of the problem to solve it. The nature of the relationship between the input and the output parameters is captured by means of learning the samples in the data set (Ornek et al, 2012).

One of the most commonly implemented ANNs is the Multi-Layer Perceptron (MLP) technique. The MLP is a universal function approximator, as proven by the Cybenko theorem. A MLP consists of several layers of nodes in a directed graph that is completely connected from one layer to the next. Except for the input nodes, each node is a neuron or processing element with a non-linear transfer function. MLP is a modification of the standard linear perceptron, which can differentiate data that is not linearly separable (Cybenko, 1989). MLP employs a supervised learning technique called Back-

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Propagation (BP) for training the network, and is a kind of feed-forward ANN model (Mahdevari and Torabi, 2012).

For multilayer perceptrons (MLPs), which are the most commonly used ANNs in geotechnical engineering, the processing elements are usually arranged in layers: An input layer, an output layer, and one or more intermediate layers called hidden layers (Figure 1). Each processing element in a specific layer is fully or partially connected to many other processing elements via weighted connections. The scalar weights determine the strength of the connections between the interconnected neurons. A zero weight refers to no connection between two neurons, and a negative weight refers to a prohibitive relationship. From many other processing elements, an individual processing element receives its weighted inputs, which are summed, and a bias unit or threshold is added or subtracted. The bias unit is used to scale the input to a useful range to improve the convergence properties of the neural network. The result of this combined summation is passed through a transfer function to produce the output of the processing element. For node *j*, this process is summarized in Equations 1 and 2 and illustrated in Figure1.

$$I_j = \theta_j + \sum_{i=1}^{n} w_{ji} x_i \quad (1)$$

$$y_i = f(I_j) \quad (2)$$

where I_j: is the activation level of node *j*; w_{ji}: is the connection weight between nodes *j* and *i*; x_i: is the input from node *i*, *i*,…, 1, 0= *n*; θ_j: is

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the bias or threshold for node *j*; y_i: is the output of node *j* and *f(.)*: is the transfer function (Shahin et al, 2008).

The transfer functions are designed to map a neuron or layer-net output to its actual output. The type of these transfer functions depends on the purpose of the neural network. Linear (PURELIN) and Nonlinear (LOGSIG, TANSIG) functions can be used as transfer functions (Figure 2). As is known, a linear function satisfies the superposition concept. The function is shown in Figure 2a. The mathematical equation for the linear function can be written as:

$$y = f(x) = \alpha.x \tag{3}$$

Where α: is the slope of the linear function. As shown in Figure 2b, sigmoidal (S shape) function is the most common nonlinear type of the activation used to construct the neural networks. It is mathematically well-behaved, differentiable, and a strictly increasing function. A sigmoidal transfer function can be written as equation 4.

$$f(x) = \frac{1}{1+e^{-cx}}, 0 \le f(x) \le 1 \tag{4}$$

Where *c*: is the shape parameter of the sigmoid function. The *c* parameter is a constant that typically varies between 0.01 and 1.0. By varying this parameter, different shapes of the function can be obtained as illustrated in Figure 2b; *x*: is the weighted sum of the inputs for a processing unit. This function is continuous and differentiable. Tangent sigmoidal function is described by the following mathematical form (Figure 2c) (Park, 2011):

$$f(x) = \frac{2}{1+e^{-cx}} - 1, -1 \le f(x) \le +1 \tag{5}$$

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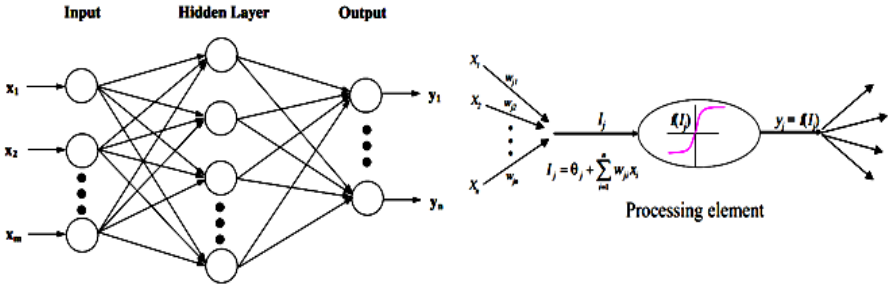


Figure 1. Typical structure and operation of ANNs

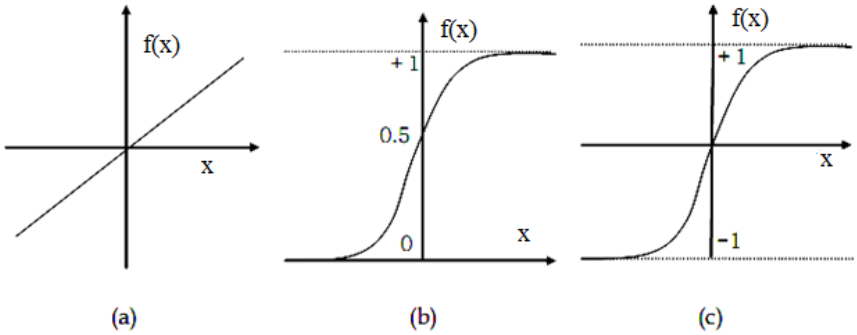


Figure 2. Transfer Function

The propagation of information in the MLP starts at the input layer, where the network is presented with an actual measured set of input data. The actual output of the network is compared with the desired output, and an error can be calculated. Using this error and utilizing a learning rule, the network adjusts its weights until some stopping criterion is met, so that the network can obtain a set of weights that will produce the input/output mapping that provides the smallest possible error. This process is known as ‘‘learning” and ‘‘training”. One common stopping criterion that will be used for the development of MLP model in this paper, is the cross-validation technique proposed by Stone, which is considered to be the most valuable tool to ensure that overfitting does not occur. Cross-validation requires data,

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be divided into three sets: training, testing and validation. The training set is used to adjust the connection weights. The testing set is used to determine when to stop training to avoid overfitting. The validation set is used to test the predictive ability of the model in the deployed environment (Stone, 1974).

Case Study

Mashhad Metro is a light rail system operating in the holy city of Mashhad, in the Khorasan Razavi province of Iran. The city of Mashhad is spread over 270 Km², and has a population of 5.2 million. Comprehensive studies for the construction of a new urban railway line were conducted during 1994-1999 and 2002-2004, highlighting the requirement for four new urban rail lines in Mashhad. Line 2 of Mashhad Metro extending from Koohsangi to Tabarsi, will be a heavy metro, and include 12 underground stations (Figure 3). This line has been realized with TBM technique. Total length of Line 2 is approximately 14.3 Km, in which 14 Km is underground. Line 2 will provide connections to the existing metro Line 1, and future Line 3 and Line 4, as well as the national railway line of Iran. Geotechnical profile of path of Line 2 is shown in Figure 4.

Artificial Neural Networks for Predicting Tunnelling-Induced Surface Settlement

Network architecture

Determining the network architecture is one of the most important and difficult tasks in ANN model development. It requires the

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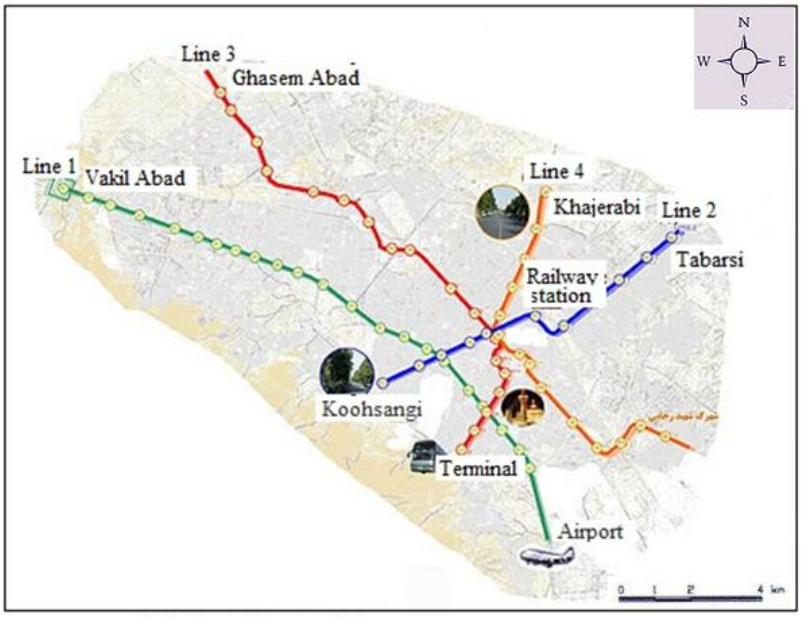


Figure 3. Location of Mashhad subway tunnels

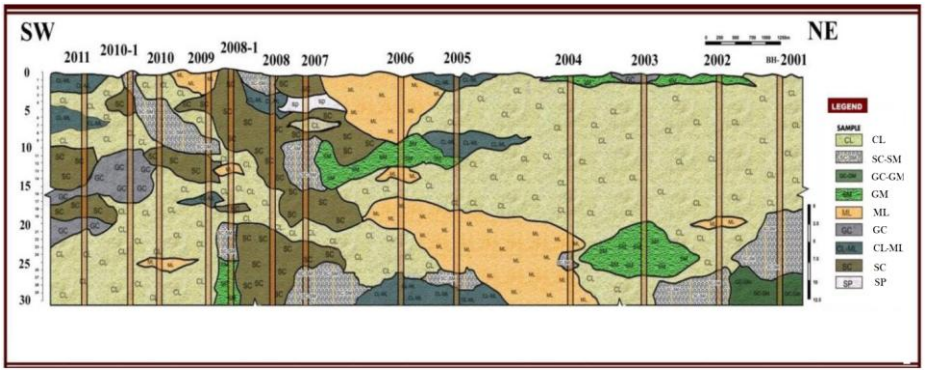


Figure 4. Geotechnicl profile of path of Line 2

selection of the optimum number of layers and the number of nodes in each of these. There is no unified approach for the determination of an optimal ANN architecture. It is generally achieved by fixing the number of layers and choosing the number of nodes in each layer. For

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MLPs, there are always two layers representing the input and output variables in any neural network. It has been shown that one hidden layer is sufficient to approximate any continuous function provided that sufficient connection weights are given (Hornik, 1989). In addition, some researchers stated that the use of more than one hidden layer provides the flexibility needed to model complex functions in many situations (Shahin et al, 2008). Lapedes and Farber provided more practical proof that two hidden layers are sufficient, and according to Chester, the first hidden layer is used to extract the local features of the input patterns while the second hidden layer is useful to extract the global features of the training patterns (Lapedes and Farber, 1988; Chester, 1990). However, Masters (1993) stated that using more than one hidden layer often slows the training process dramatically and increases the chance of getting trapped in local minima.

The number of nodes in the input and output layers is restricted by the number of model inputs and outputs, respectively. There is no direct and precise way of determining the best number of nodes in each hidden layer. A trial-and-error procedure can be used to determine the number and connectivity of the hidden layer nodes. It has been shown in the literature that neural networks with a large number of free parameters (connection weights) are more subject to overfitting and poor generalization. Consequently, keeping the number of hidden nodes to a minimum, provided that satisfactory

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performance is achieved, is always better, as it: (a) reduces the computational time needed for training; (b) helps the network achieve better generalization performance; (c) helps avoid the problem of overfitting, and (d) allows the trained network to be analyzed more easily (Shahin et al, 2008).

In our case, the ANN architecture has been tested with various numbers of hidden layers and nodes per hidden layers, and the ANN parameters are checked with logistic sigmoid (logsig) transformation function to find better values and architecture.

Input parameters

An important step in developing ANN models is to select the model input variables that have the most significant impact on model performance. A good subset of input variables can substantially improve the model performance.

It is difficult to determine all the relevant parameters that influence the prediction of tunnelling-induced surface settlement. The selected parameters affecting tunnelling-induced surface settlement which are used in this study were: distance from the entrance of the tunnel; (L), depth of the tunnel; (D), density of the soil; (γ), modulus of elasticity of the soil; (E), cohesion of soil; (C), internal friction angle of soil; (ϕ), and earth pressure balance; (EPB).

Data preparation

Before training and implementing, the data set was divided randomly into training, validation, and test subsets. In the present study, the data sets of 181

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data from surface settlement recorded in line 2 of Mashhad subway tunnel project were collected. Table 1 presents the range of the data used in this study.

Table 1. The range of the data

Variable category	Parameter	Symbol	Minimum	Maximum	Average
Input	Internal friction angle of soil (Degree)	ϕ	25.000	40.000	29.470
	Cohesion of soil (Kg/cm^2)	C	0.000	0.300	0.194
	Modulus of elasticity of soil (Kg/cm^2)	E	70.000	450.000	203.481
	Density of soil (KN/m^3)	γ	15.500	22.000	19.439
	Earth pressure balance (Bar)	EPB	0.109	1.965	1.252
	Depth of the tunnel (m)	D	13.940	23.120	16.395
	Distance from the entrance of the tunnel (m)	L	23.000	899.000	359.074
Output	Surface settlement (m)	δ	-0.030	0.001	-0.004

From these, 70% of the data were chosen for training, 15% for validation, and 15% for the final test. The training set was used to generate the model, and the validation set was used to check the generalization capability of the model. Once the available data have been divided into their subsets (i.e., training, testing, and validation), it is important to pre-process the data in a suitable form before applying them to the ANN. Data pre-processing is necessary to ensure that all variables receive equal attention during the training process (Maier and Dandy, 2000). Moreover, pre-processing usually speeds up the learning process. Pre-processing can be in the form of data scaling, normalization, and transformation (Masters, 1993).

In this study the input and output data were scaled to lie between 0 and 1, by using Equation 6:

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$$x_{norm} = 0.5(\frac{x - \bar{x}}{x_{\max} - x_{\min}}) + 0.5 \quad (6)$$

Where x_{norm}: is the normalized value, x: is the actual value, $\bar{x}$: is average of value, $x_{\max}$: is the maximum value, and $x_{\min}$: is the minimum value.

Training of the network

During the training phase, data consisting of input and associated output pairs that represent the problem at hand, are processed with the network. Various algorithms are available for training of neural networks, but the back-propagation algorithm is the most versatile and robust technique. It provides the most efficient learning procedure for multilayer perception neural networks (Gholamnejad and Tayarani, 2010). The back-propagation learning algorithm has been applied with great success to model many phenomena in the field of geotechnical engineering (Shahin et al, 2008).

Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between given input and output vectors. A forward pass is made during training when data is processed through the input layer to the hidden layer and thence to the output layer. During the backward pass the network's actual output (from the previous forward pass) is compared to the target output. Error estimates are computed from the comparison. The weight associated with an output unit can be adjusted to reduce the error. This process is repeated for all training pairs in the data set until the network error converges to a threshold (minimum error) defined by some corresponding cost function (Cybenko, 1989). Several

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training algorithms of back-propagation have been developed (for example; Gradient descent and Levenberg-Marquardt) (Mohammadi and Mirabedini, 2014). In this study the Levenberg-Marquardt back-propagation algorithm was chosen for training the ANNs, because it is known to be the fastest method for training moderate-sized feed-forward neural networks.

Validation and testing the ANN model

Once the training phase of the model has been successfully accomplished, the performance of the trained model should be validated. The purpose of the model validation phase is to ensure that the model has the ability to generalize within the limits set by the training data in a robust fashion, rather than simply having memorized the input-output relationships that are contained in the training data.

Testing and validation of the ANN model was done with new data sets. These data were not previously used while training the network. The Mean Squared Error (MSE) and coefficient of correlation factor (R) between the predicted and measured values were taken as the performance measures. The MSE was calculated as:

$$MSE = \frac{1}{Q}\sum_{Q}(d - o)^2 \quad (7)$$

Where d, o, and Q; represent the target output, the output, and the number of input-output data pairs, respectively.

Results and Discussion

As there is no direct and precise way of determining the most appropriate number of hidden layers and number of neurons in each

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hidden layer, a trial and error procedure is typically used to identify the best network for a particular problem (Gholamnejad and Tayarani, 2010). After building several MLP models based on trial and error, the best results of each model are compared, and the one with the maximum correlation factor (R), and minimum Mean Squared Error (MSE) is chosen. The result are listed in Table 2 and shown in Figure 5 and Figure 6.

Therefore, based on these criteria, the optimum ANN architecture was found to be a three-layer, feed-forward, and back-propagation neural network with a topology of 7-24-1. As shown in Table 2, for optimum ANN architecture, the correlation factor and minimum of Mean Squared Error are 0.963 and 2.41E-04, respectively.

Table2. Performance of the neural network models

Model Number	Network Architecture	Data set							
		Training		Validation		Testing		ALL	
		MSE	R	MSE	R	MSE	R	MSE	R
1	7*4*1	5.2372E-04	0.929	4.6969E-04	0.880	5.2757E-04	0.846	5.1623E-04	0.918
2	7*8*1	4.6363E-04	0.935	6.1394E-04	0.762	1.0000E-03	0.823	5.6917E-04	0.910
3	7*12*1	4.3002E-04	0.942	9.8094E-04	0.776	4.6030E-04	0.873	5.1672E-04	0.918
4	7*16*1	4.4344E-04	0.936	6.3672E-04	0.804	4.0745E-04	0.946	4.6690E-04	0.926
5	7*20*1	6.0997E-04	0.914	4.7938E-04	0.915	5.4108E-04	0.844	5.8021E-04	0.908
6	**7*24*1**	**1.56E-04**	**0.979**	**5.81E-04**	**0.839**	**2.98E-04**	**0.955**	**2.41E-04**	**0.963**
7	7*28*1	3.3069E-04	0.955	5.2859E-04	0.897	6.3572E-04	0.800	4.0571E-04	0.936
8	7*32*1	5.5986E-04	0.927	3.1418E-04	0.834	5.1557E-04	0.830	5.1660E-04	0.918
9	7*8*4*1	3.7419E-04	0.919	9.2781E-04	0.948	1.1000E-03	0.753	5.6256E-04	0.910
10	7*12*8*1	6.4642E-04	0.911	7.7318E-04	0.839	6.0904E-04	0.796	6.5975E-04	0.895
11	7*16*12*1	4.8208E-04	0.928	2.7959E-04	0.940	8.3221E-04	0.909	5.0410E-04	0.921
12	7*20*16*1	4.3242E-04	0.940	6.3950E-04	0.828	6.5465E-04	0.854	4.9646E-04	0.921
13	7*24*20*1	2.3051E-04	0.964	5.4883E-04	0.889	4.7688E-04	0.951	3.1475E-04	0.951

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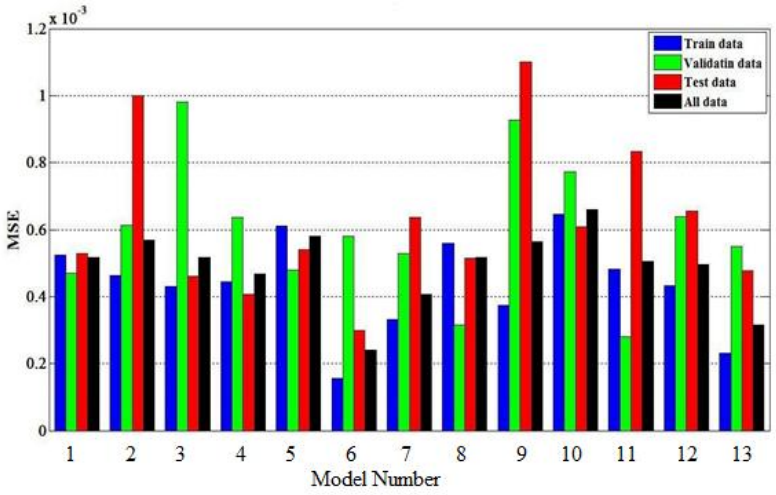


Figure 5. Mean Squared Error of different ANN models

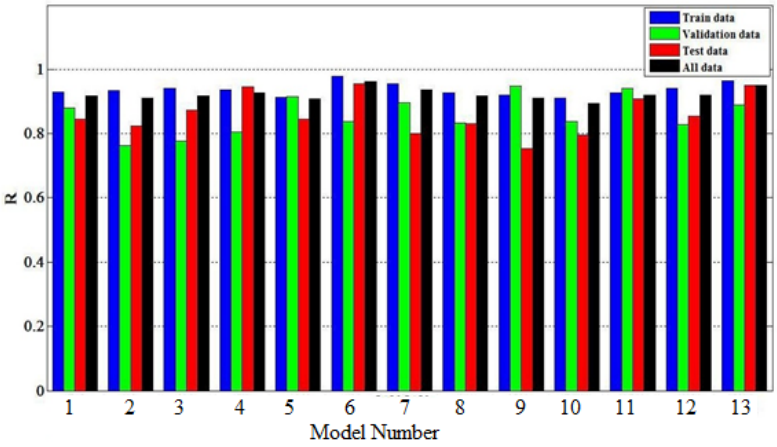


Figure 6. Correlation factor of different ANN models

Figure 7 shows the correlation coefficient between the measured and predicted deformation for the optimum model, and Figure 8 shows a graph comparing the measured and predicted data for the optimum ANN model. It appears that the optimum model has predicted values close to the measured ones.

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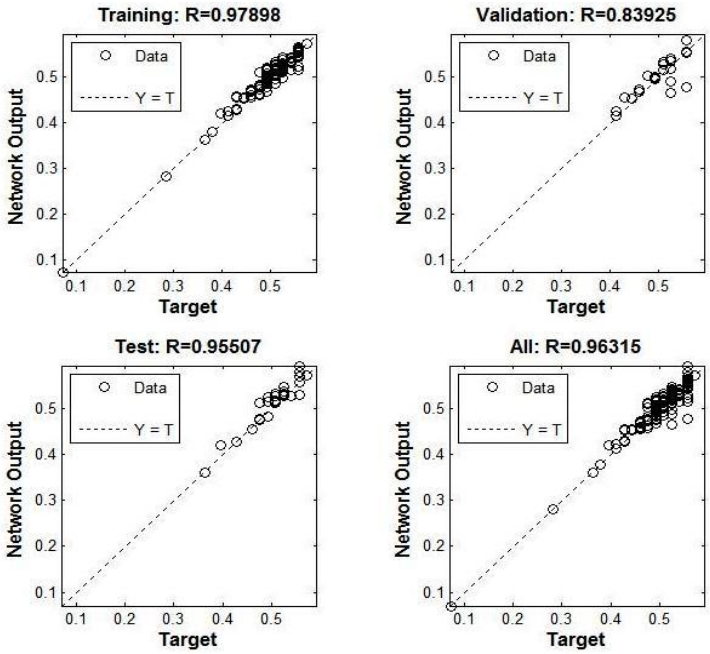


Figure 7. Correlation factor between measured and predicted surface Settlement

The presented analysis showed that, based on the available excavation data, artificial neural networks can be a useful tool to predict the displacements induced by the TBM. It must be stressed that the proposed methodology does not require any priori assumption on the shape of the settlement trough, or on the relations between settlements and TBM operation parameters. The results obtained are acceptable even when in the considered case study the measured displacements are relatively small compared to the measurement accuracy. This type of analysis can be employed to determine, on a specific case, the required phenomenon or features to take into account in complex numerical models at a design phase. The

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developed methodology should be applied in the analysis of other cases of tunnel excavations in other geological contexts and/or with other types of TBM.

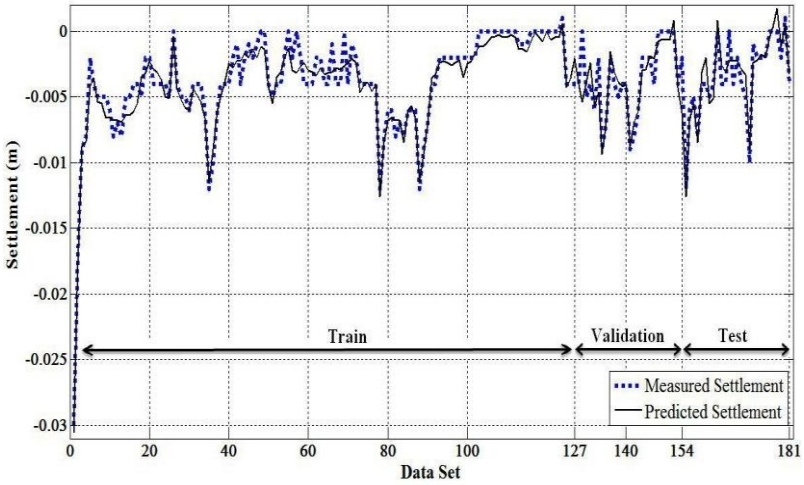


Figure 8. Comparison between measured and predicted surface settlement

Conclusions

This study investigated the potential of Artificial Neural Networks (ANN) for predicting tunnelling-induced surface settlement. It was found that the feed-forward, and the back-propagation neural network models successfully learned from the training samples in a manner in which their outputs converged to values very close to the desired outputs. However, the relationship among the inputs and outputs is very complex. The results obtained are still highly encouraging and satisfactory. The optimum ANN architecture was found to be a three-layer, feed-forward, back-propagation neural network with a topology

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of 7-24-1. As a neural network can update “its” knowledge over time, if more training data sets are processed, the neural networks will result in greater accuracy and more robust prediction than any other analysis technique. With regard to the fact that the accuracy of the proposed ANN model is reasonably high, this model can be used to predict tunnelling-induced surface settlement.

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