

Application of Neural Network for the Prediction of Settlements above Tunnels

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Abstract

This paper intends to predict settlement above tunnels with artificial neural networks. The settlement is taken as a function of diameter, depth, and volume of soil loss, apart from soil strength, groundwater characteristic and construction methods. The output variables are settlement and trough width. A three layered backpropagation neural network is designed, trained and tested with parameters obtained from the detailed investigation of different tunnel projects published in literatures. The three-layered perceptron predicts reasonably accurate settlement after learning from examples derived from the observation data.

1 Introduction

In order to minimize risk of damage from tunneling, 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. Many environmental factors associated with tunneling have recently led to a considerable research effort being devoted to the study of settlements caused by tunneling through soft ground.

A settlement prediction method should be based on the effect of a number of parameters, such as soil strength, groundwater condition, tunnel depth, opening diameter, construction methods, excavated volume of tunnel and volume of soil loss. The ground condition and construction methods both determine volume of ground loss that results

from tunneling [1]. The traditional concept of ground loss parameter may sometimes be redefined as equivalent ground loss parameter with respect to gap parameter [2].

Progress has been made in recent years in our ability to predict ground movements, but the state of art is deficient in many ways. To improve the reliability of prediction, it is necessary to build a body of experiences based on documented case histories and to fit it into a conceptual frame work that will allow the development of empirical and semi empirical cause and effect relations. In this paper, measurements of settlement and ground movements made on different tunnel projects have been reviewed and analyzed. The data from these case studies are used to train and test the developed neural network model to enable prediction of the magnitude of settlements and ground movements with the help of input variables that have direct physical significance.

2 Background

The assessment of settlement problem associated with soft ground tunneling can be distributed into three steps: the prediction of the ground loss in the tunneling process, the prediction of ground movements generated by these losses, and the assessment of possible distress to infrastructures and facilities brought about by these ground movements. Of these, the first and most difficult task is the prediction of the ground losses in the tunneling process.

Construction of a tunnel in soft ground brings about a change in the state of stress and corresponding strains and displacement around the tunnel opening. Therefore, some degree of settlement of the overlying ground surface

may always be induced. To make reliable forecast of the inevitable settlements associated with every design or construction procedures that might reasonably be adopted for the work, proper consideration as to type of soil, groundwater conditions geometry and depth of tunnel, etc. is necessary [3].

2.1 Ground losses

When an estimate of ground losses has to be made, it is convenient to separate the estimate into three items namely the elastic movements (unavoidable loss, the nominal face loss (tail void loss) and the curvature loss. Extraordinary loss is due to excessive pitch and yaw or due to excessive plowing of face [3].

For the displacement around an unsupported tunnel heading in an elastoplastic material, the radial volume of lost ground per unit length of tunnel (V_L) is approximately related to the volume of ground lost axially in to the face by: $V_L = V_{axial}(2/R)$. The ground loss (V_L) is often expressed as a percentage of the excavated volume. The relation is valid for most of the soils including granular soils and stiff to hard clay [4].

For ground movement that occurs at a constant rate into the face, the radial loss of ground is a function of the rate of advance of the tunnel and the rate of the extrusion of the soil. This would be applicable where the stability ratio is high, and the time dependent displacements are taking place. Ground loss over Shield has also been associated with appendages (cutters, bead or teeth) which cut larger diameter than the body of shield. The loss of ground over the shield also develops when the pitch or yaw of the shield is different from its grade or line.

A number of empirical and semi empirical relationships have been developed for estimating the ground loss. Schmidt, for example, presented an equation for the relative lost ground volume in the inelastic range as a function of undrained shear strength, elasticity and overburden pressure. It was also concluded for an elastic medium, the ground loss is less than 0.2 to 0.6 percentage of the excavated

volume [6]. Peck (1969) suggested that the magnitude of volume of ground loss into tunnel depend on stability number (N) given by:

$$V_L = f\left(\frac{P_z - P_a}{S_u}\right) = f(N) \tag{1},$$

where P_z is total vertical pressure at a depth of Z (centre of tunnel) P_a is air pressure above atmosphere and S_u describes undrained shear strength of clay [5]. Atkinson & Potts (1977) approximated a ratio of the volume of ground lost at the surface and at the tunnel face; knowing the face settlement, surface settlement could be estimated using the established relation [6].

2.2 Prediction of Ground Movement

Many studies have been done for the prediction of ground movement. Most of these studies have followed, at large, the trend set by Peck (1969) who represented the settlement trough over a single tunnel by the error function normal curve or probability curve within reasonable limits [7].

$$S = S_{max} \exp\left(-\frac{x^2}{2i^2}\right) \tag{2},$$

where S is the surface settlement at transverse distance x from the tunnel centerline. The settlement trough and detail nomenclature has been displayed in Figure 1. The settlement curve is completely defined by two unknown parameters i and S_{max} .

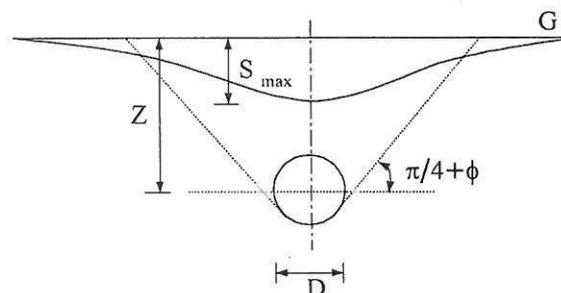


Fig. 1 Typical section of tunnel

2.2.1 Estimation of Point of Inflection

A significant number of researches involving statistical models of field data are devoted to estimate the point of inflection. Peck collected and plotted relationship between width of settlement trough, as represented by i/R (i.e. the inflection-radius ratio), against depth ratio ($Z/2R$) for various tunnels in different materials [5]. Schmidt derived an empirical relationship for quantity 'i' for the tunnels in cohesive soil as a function of depth and tunnel radius [3]. Atkinson and Potts determined a relationship between point of inflection, tunnel dimension and the tunnel center line depth, from model tests and field measurement in sand. Two such relationships were presented in normal sand without surface surcharge, and in dense sand and overconsolidated Kaoline clay with surface surcharge loading [6]. A stochastic model analysis carried out by Norgrove et al. (1979) also expressed inflection-radius ratio (i/R) as a function of depth-diameter ($Z/2R$). The relation was supported by many case history data [7]. However, studies by O' Reilly and New showed that the trough width is a function of depth alone and can be expressed with a simple relationship $i = KZ$ for all practical purposes, where the value for K is taken as 0.5 for cohesive soils 0.25 for granular soils [1]. Wang and Chang have recently presented empirical formulae to estimate the point of inflection and correlated it with depth of tunnel and its dimension.[8].

2.2.2 Estimation of Maximum Settlement

If the settlement trough is represented by an error function or probability curve, the maximum settlement S_{max} can be derived from a simple integration and expressed as:

$$S_{max} = \frac{V_s}{2.5i} \quad (3),$$

where V_s is the volume of settlement trough per unit length along tunnel axis [7]. Several researchers attempted to correlate (V_s) to the

volume of ground loss during excavation (V_L) or to the excavated tunnel volume (V_{exc}).

Maximum settlement can also be estimated from the settlement ratio (S_{max}/S_c). If the settlement ratio is established through empirical correlation, knowing the vertical displacement above the tunnel crown (S_c), maximum surface settlement (S_{max}) can be estimated from the relationship as established [4]. Based on the model test and field observations Atkinson & Potts proposed a relationship between the settlements at the ground surface and at the crown for shallow tunnels of limited depth ratio (Z/R). Once the crown settlement is known from observation, the relationship can be used to estimate the surface settlement [6].

3 Prediction of Settlement By Neural Network

Artificial neural networks are massively parallel interconnected networks of simple elements and their hierarchical organizations which are intended to interact with the objects of the real world in the same way as biological nervous systems do. A neural network uses previously solved example to build a system of 'neurons' that makes new decisions, classifications and forecasts. Neurons are the fundamental building block for a neural network. Vast numbers of literatures are available on neural networks (See Wasserman, 1989) [9].

Developed by Rumalhart et al., backpropagation is a systematic method for training multilayer neural networks. It is an algorithm to minimize the mean squared error. Backpropagation method uses a set of input and output patterns. The number of hidden layers and neurons in it are determined by hit and trial. An input pattern is used by the system to produce an output, which then is compared with the actual output. If there is no difference, then no learning takes place. Otherwise, if there is difference, the weights are changed backward to reduce difference [10].

Many interesting results using backpropagation method have been obtained. Stone found that the learning process was

determined by the correlation between the input patterns, and not by the specific pattern used. [11]. Rumelhart et al. and Wasserman applied backpropagation in solving many problems including classic the XOR problem, parity problem, etc. [9, 10].

Although many successful applications using backpropagation method have been reported, only a few of them are in geotechnical field. Agrawal et al. introduced backpropagation neural network for data analysis and modeling [12]. Kojiri & Nishimura proposed a prediction system of rainfall and landslide with neural networks [13]. Lee & Lee applied backpropagation neural networks to predict the pile bearing capacity [14]. Goh et al. presented backpropagation neural networks to estimate the lateral wall movements in braced excavations and demonstrated that the neural networks could synthesize data derived from finite element studies on braced excavations in clays and capture the nonlinear interactions between the variables in the system analysis [15].

Ghaboussi & Sidarata developed new nested adaptive neural networks (NANN) for constitutive modeling and trained directly with the results of material tests, to analysis the boundary value problems similar to any other material model [16]. Shi et al. presented a modular back propagation neural networks for predicting the settlement during tunneling by integrating multiple NN models in one system; each model being constrained to operate at one specific situation of a complicated real world problem [17].

4. Neural Network Model

To solve a real field problem using artificial neural networks, it is required that the problem be analyzed to select appropriate network architecture. This is done by determining the number of hidden layers and the number of neurons in various layers, choosing an appropriate activation function, defining data scaling and training method to arrive at the desired error goal. The number of neurons in input and output layers is usually

dictated by the nature of the problem. In this specific problem the number of input variables are determined as a function of settlement of tunnel diameter, depth to axis, volume of soil loss, soil strength properties, groundwater characteristic and construction methods and output variable as settlement

The convergence performance of the network was found to be optimal with 5 neurons in hidden layer. Only one hidden layer was found suitable, and thus a three layers network architecture with 6 input neurons, 5 hidden neurons and one output neuron is adapted as shown in figure 1.

4.1 Input Variables

Prediction of ground behavior above tunnels has been a subject of research for long. A number of comprehensive works have been done based on empirical relationships; some of these relationships are presented in table 1. Based on these existing models, a number of input parameters are identified namely D , Z , V_s , soil type (soil strength). Effect of ground water level and construction method on soil behavior has also been incorporated. Although the hydraulic conductivity of clay is small, the ground water level will greatly affect the overburden pressure on tunnel crown.

Parameter variables used in this study are taken from already published literatures and include various case studies of tunnel projects of different countries as stated in Table 2. These data were reviewed and analyzed to be presented in the network. The tunnel diameter (D), depth of tunnel axis from ground level (Z) and volume loss induced by tunneling per meter (V_s) have been used in readymade form. The ground water characteristic and construction methods are worked out as required to input in neural networks. The ground water level is classified in to two categories, the water level above the tunnel crest is taken as 1 and below tunnel axis is taken as 2. Similarly the construction methods are also classified as 1, 2, and 3 for hand-mined shield, mechanical shield and semi-mechanical type (compressed air support) shield respectively. For the soil strength properties

undrained shear strength (C_u) and angle of internal friction (ϕ) are used as available, and estimated using empirical relations from standard penetration number (N) when necessary [18].

Table 1. Various empirical models for prediction of settlement above tunnel.

Model	Parameters	References
$S_{max} = \frac{V_s}{2.5i}$	V_s, i	General (20)
$S_{max} = f\left(\frac{z}{2R}\right)$	Z, R	Attewell & Farmer (3)
$V_s = \sqrt{2\pi} S_{max} i_0$	S_{max}, i_0	Yoshikoshi et al (3)
$\frac{V_s}{V_L} = 2\sqrt{\frac{2}{\pi}} \left(\frac{i}{2R}\right) \left(\frac{S_{Max}}{S_C}\right)$	V_s, V_L, S_{Max}, S_C	Atkinson & Potts (3)
$i_o = k_o^* z_o, \frac{V_s}{V_{exe}} = m^*$	I, Z	O'Reilly & New (3)
$i_o = 0.8D \left(\frac{z_o - z}{D}\right)^{0.4}$	D, Z	Moh et al. (19)
$i_o = \left(\frac{D}{2}\right) \left(\frac{Z_o}{D}\right)^{0.8}$	D, Z	Clough & Schmidt (3)
$\frac{i}{R} = f\left(\frac{z}{2R}\right)$	Z, I, R	Peck (20)

$k^* m^*$ are functions of soil types.

The investigation works conducted for different model show that, the trough width and tunnel settlement are the function of parameters as soil strength properties, tunnel depth, tunnel size, volume loss etc. So on this basis, the parameters as input variables for the prediction of settlement by neural network has been choose. In order to predict the settlement over tunnels as accurate as possible some more input parameters as construction method and ground water level has also been incorporated, which are also considered as main factors together

with above mentioned parameters for settlement prediction.

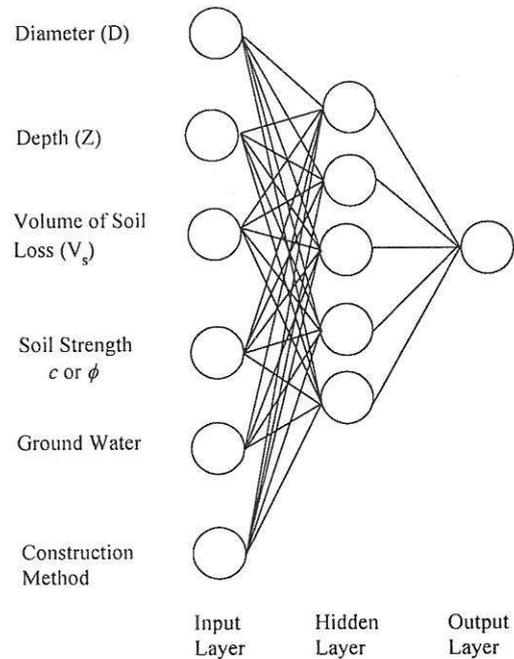


Fig.2 Neural network model

Before the network training, weights were initialized to small random values and inputs were scaled to the value of similar magnitude to reduce any chance of prematurely saturating the sigmoidal neurons and thus slowing the training. The sigmoidal activation function used as:

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

In backpropagation neural networks model, the data used consists of two sets, one for training and the other for testing the model. In this case, even patterns of input/output variables were used for training and an odd number of patterns for testing. The sample data used for training and testing the networks are presented in Table 2.

5. Results and Discussion

The objective of this study is to predict the settlement and point of inflection (trough

width) with the help of input variables that have direct physical significance. As per different models mentioned in table.1 a functional relationship of settlement with the tunnel diameter, soil properties (undrained shear strength) and normalized volume loss individually has been established for the input and output parameters as shown in figures 3,4 and 5.

The network architecture with 5 hidden and one-output neurons was found optimal for this study. A hit and trial method with the learning rate of 0.1, 0.05 and 0.001, was conducted in order to achieve the desired error goal of 15% (Fig. 3).

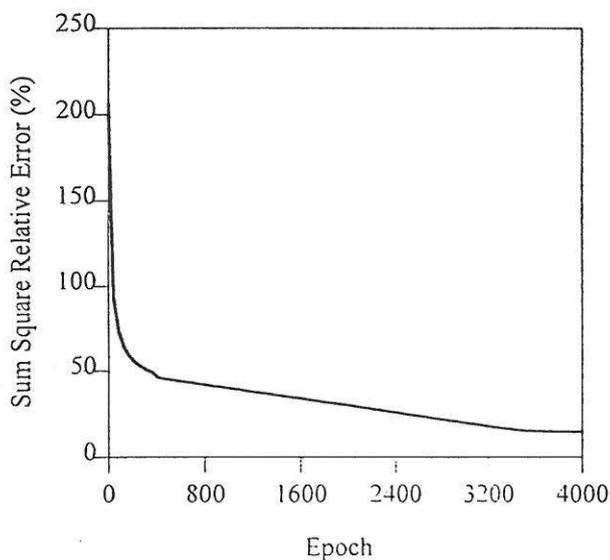


Fig. 3 Variation of sum square relative error in settlement prediction

5.1 Prediction of Maximum Settlement

The network trained for the prediction of maximum settlement was found to have converged in 4,000 iterations meeting the error goal at the learning rate of 0.05. At the learning rate of 0.1, the error goal of 15% was not met even after 40000 iterations. The variation of error with the number of network epochs resulting from training data set has been displayed in figure 3. The sum squared relative error reduces sharply at first and gradually stabilizes after 4000 iterations.

A comparison of target and predicted outputs of the testing is presented in figure 4.

the simulated result fairly accurately predicts the settlement expect at some bias points. Anomalies between observed and predicted values are particularly significant for Toronto subway data. The observed result could not be explained with available information but it has been reported that the tunnel sides and inverts are in till and the crown of the tunnel is in water bearing sand. Barring this, the results from the testing of independent data shows that the network is fairly able to generalize the output provided that the input variables are within the range of data used in training set.

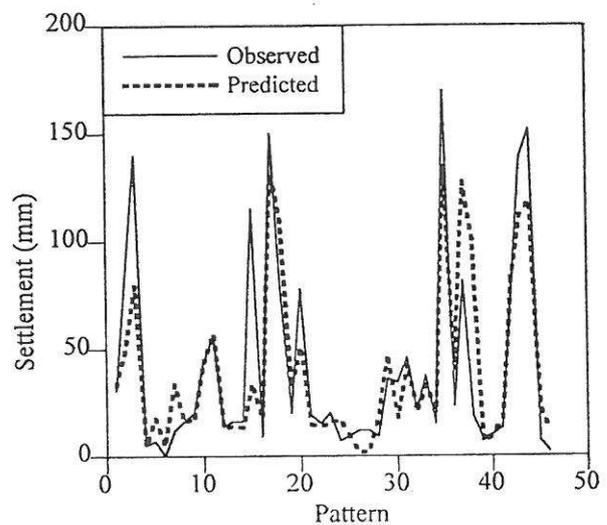


Fig.4 Prediction of maximum settlement

The neural network model establishes complex relationship among various parameters involved. The relationship between any single parameter and the prediction of settlement may not be the explained with one to one linear expression accurately. However an attempt has been made to present the predicted result as a function of these parameters, which has more physical significance.

The relationship between maximum settlement and tunnel size has been illustrated in figure 5, which shows that the predicted settlement increases with increase in tunnel size.

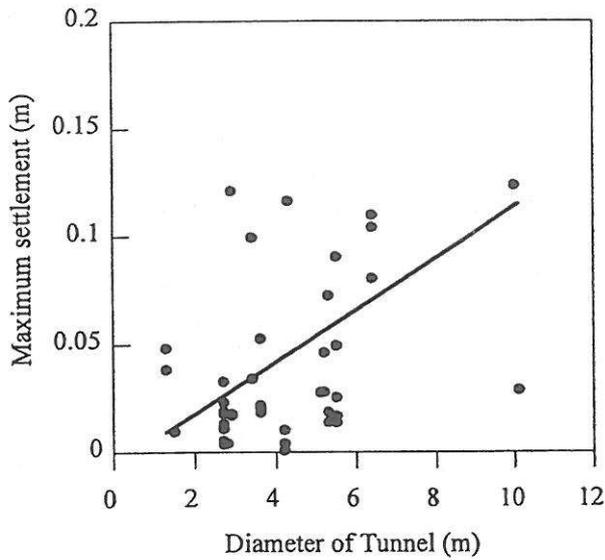


Fig. 5 Maximum settlement as a function of tunnel size.

Figure 6 shows settlement as a function of soil strength properties. If only the predicted results from clayey tunnel are taken and plotted as undrained shear strength versus predicted settlement, a line with negative slope can be fitted as shown in figure 6. It is but logical that as strength increases settlement decreases. Similarly, relationship between predicted settlement and normalized volume loss is shown in figure 7.

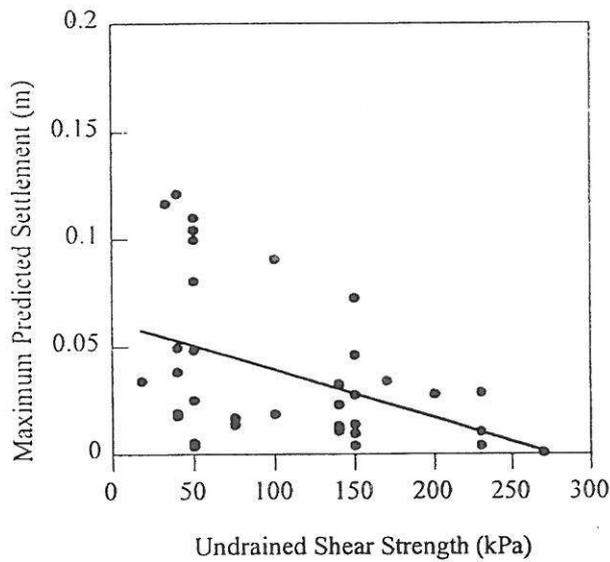


Fig. 6 Predicted settlement versus undrained shear strength of clay

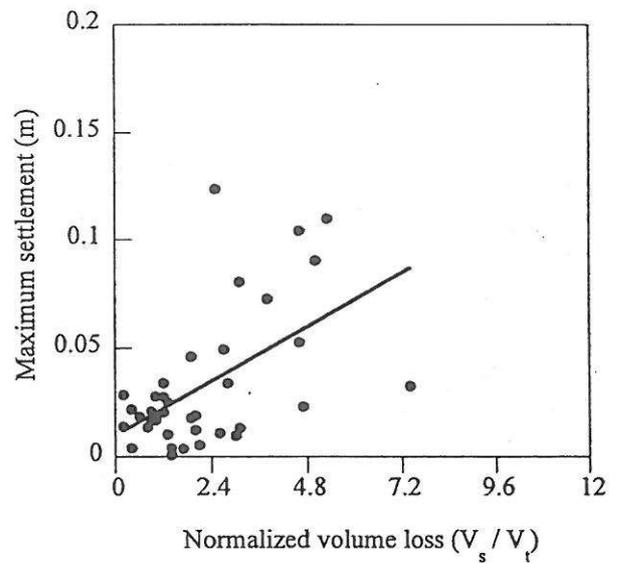


Fig.7 Maximum settlement versus normalized volume loss

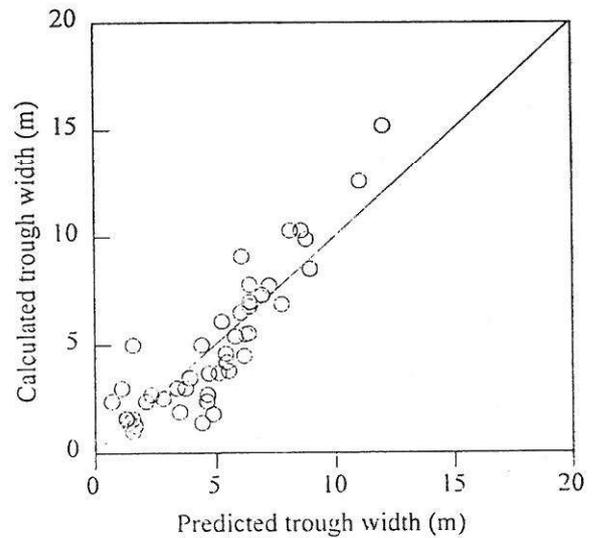


Fig 8. Predicted versus observed trough width

5.2 Prediction of Inflection

For the prediction of trough width, observed maximum settlement (S_{max}) was added to input layers making seven variables in total. With five neurons in hidden layer, the network is trained and tested for the prediction of trough width. The conversion of network and influence of learning rate was found. A comparison of target and predicted outputs of the testing is presented in Figure 5. The result shows that the predicted inflection (i) with

neural network gives more accurate results than that of calculated.

6. Conclusion

A backpropagation neural network was developed to predict settlement and trough width of a tunnel. The neural network demonstrated a promising result and predicted the settlement and trough width of a tunnel fairly successfully. If input variables influencing output goals are clearly identified and if a descent number of quality data are available, backpropagation neural network can be successfully used as a mapping and prediction tools in geotechnical perspective.

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Table 2 Sample training and testing data

S.N	References	Location	Depth to axis, Z, (m)	Tunnel dia (m)	Vol loss, Vs, (m ³)	GW level 1 or 2	(Cu) kN/m ² , or (ϕ^0)	Construction method	Settlement S _{max} , (m)	Trough width, i (m)
1	[7]	Toronto Subway (Canada)	11.9	5.2	0.2	2.0	49 ^u (s)	1.0	30.5	2.7
2	[7]	As above 1st tunnel	10.4	5.2	0.4	2.0	49 ^u (s)	1.0	85.0	1.9
3	[7]	As above 2nd tunnel	13.4	5.3	0.9	2.0	49 ^u (s)	1.0	140.0	2.4
4	[1]	Regents Park London UK	34.0	4.2	0.2	2.0	230.0	1.0	5.0	15.2
5	[1]	Regents Park London UK	20.0	4.2	0.2	2.0	230.0	1.0	7.0	10.3
6	[1]	As above Green park	29.3	4.2	0.2	2.0	270.0	1.0	0.2	12.6
7	[1]	Heathrow tunnel UK	13.3	10.1	0.2	2.0	230.0	1.0	12.0	6.5
8	[1]	Belfast sewer UK	4.9	2.7	0.1	1.0	40.0	1.0	16.0	2.7
9	[1]	Belfast sewer UK	4.5	2.7	0.1	1.0	40.0	1.0	20.0	2.4
10	[1]	Stockton sewer C' UK	6.3	1.3	0.4	2.0	40.0	1.0	43.7	3.5
11	[1]	Stockton sewer D' UK	5.9	1.3	0.5	2.0	50.0	1.0	56.3	3.7
12	[7]	Airshire drainage scheme I	6.3	2.9	0.1	2.0	0.0	1.0	13.5	1.4
13	[7]	Airshire drainage scheme I	6.1	2.9	0.1	2.0	0.0	1.0	16.0	1.6
14	[7]	As above II nd tunnel	6.2	2.9	0.1	2.0	0.0	1.0	16.0	1.6
15	[7]	Toronto Subway B4(Canada)	11.2	5.1	0.2	2.0	150.0	1.0	115.0	10.3
16	[7]	Toronto Subway B4(Canada)	13.1	5.3	0.1	2.0	100.0	1.0	9.2	6.1
17	[7]	Brussel Metro	16.0	10.0	2.0	2.0	0.0	1.0	150.0	5.5
18	[7]	NWA contract 276	13.0	3.4	1.5	1.0	50.0	1.0	78.0	7.3
19	[7]	Bristol sewerage scheme	6.0	3.4	0.3	2.0	18.0	1.0	20.0	5.0
20	[7]	WNTDC Lumbrook sewer	4.7	3.6	0.5	2.0	0.0	1.0	78.0	2.4
21	[7]	WNTDC Lumbrook sewer	9.0	3.6	0.1	2.0	0.0	1.0	19.0	2.5
22	[7]	WNTDC Lumbrook sewer	6.5	3.6	0.1	2.0	0.0	1.0	15.0	1.6
23	[7]	WNTDC Lumbrook sewer	6.5	3.6	0.1	2.0	0.0	1.0	20.0	1.0
24	[7]	WNTDC Lumbrook sewer	6.5	3.6	0.1	2.0	0.0	1.0	7.0	1.3
25	[3]	Bangkok.GBC5 project 6+609	16.5	2.7	0.1	2.0	50.0	2.0	12.0	5.6
26	[3]	Bangkok.GBC5 project 6+607	18.5	2.7	0.1	2.0	50.0	2.0	12.0	7.8
27	[3]	Bangkok.GBC5 project 6+605	16.5	2.7	0.1	2.0	50.0	2.0	12.0	7.0
28	[3]	San Francisco	11.0	5.3	0.1	2.0	150.0	2.0	9.2	1.4
29	[7]	Lower market BART	19.0	5.5	0.6	2.0	40.0	2.0	36.0	6.9
30	[7]	Sabrook sewerageUSA	13.0	2.7	0.2	2.0	140.0	2.0	34.0	1.8
31	[7]	As above sta. 37+50	13.5	2.7	0.4	2.0	140.0	2.0	46.0	3.8
32	[7]	As above sta. 39+50	13.1	2.7	0.2	2.0	140.0	2.0	21.0	3.7
33	[7]	As above sta. 43+47	10.1	2.7	0.3	2.0	140.0	2.0	37.0	3.0
34	[7]	As above sta. 45+10	9.5	2.7	0.1	2.0	140.0	2.0	15.0	3.0
35	[7]	Mexico city Siphon II	11.7	2.9	2.1	2.0	40.0	2.0	105	7.8
36	[7]	Frankfurt metro Dom platza	15.0	6.5	0.4	2.0	170.0	2.0	23.0	6.8

Note: Ground water level above and below the tunnel crest are taken as 1 and 2 respectively.
Construction methods are taken as 1 and 2 for hand mined mechanical shield respectively.
All tunnels are in clay except those marked (s) which are sand tunnels.