PREDICTION OF SUBSIDENCE BY FEM AND ANN IN SHALLOW NATM TUNNEL

Jaeho LEE[1], Yasuhiro YOKOTA[2], Hiroki IIDA[1] & Shinichi AKUTAGAWA[3]

[1]Member of JSCE, Graduate student, Kobe University
(Rokkodai 1-1, Nada, Kobe, 657-8501, Japan)
E-mail : 006d804n@y02.kobe-u.ac.jp
[2]Kajima Corporation, Japan
[3]Member of JSCE, Associate Professor, Dept. of Architecture and Civil Engineering, Kobe University
(Rokkodai 1-1, Nada-ku, Kobe, 657-8501, Japan)
E-mail : cadax@kobe-u.ac.jp

In urban area, constructions of soft ground tunnels are usually important in terms of prediction and control of surface settlement and gradient. Several approaches are readily used for prediction of the ground deformations associated with tunneling. This paper discusses the subsidence prediction using FEM analysis and Artificial Neural Network (ANN) with FEM database. This paper, firstly, investigates the application of FEM simulation using a proposed model to predict ground movement caused by tunneling of a shallow NATM tunnel in unconsolidated soil. The proposed model used here incorporates reduction of shear stiffness, as well as strain softening effects of given material strength parameters. Numerical simulation is performed with material property values, E, ν, c, and ϕ, obtained from laboratory. Some additional parametric studies are performed. FEM results shows as agree well with compare of field data. Secondly, ANN modeling is performed for subsidence prediction. ANN studies database to provide an FEM analysis result. A learned (trained) ANN model has the potential to provide accurate desired output (true output) from input data. However, once the network is trained, its running speed is very high, thereby reducing the total time consumed in the analysis. The trained ANN model is further validated by carrying out parametric studies to assess whether the model gives logical and consistent trends and a case study to verify the application to the actual NATM tunnel in prediction problem. The two methods, FEM and ANN, offer a practical way for predicting final displacement of shallow NATM tunnel, enabling rational safety management scheme to be employed.

Key Words : *NATM tunnel, strain softening analysis, Artificial Neural Network, prediction*

1. INTRODUCTION

Currently an increasing number of urban tunnels with small overburden are excavated according to the principle of the New Austrian Tunneling Method (NATM). In urban area, constructions of soft ground tunnels are usually important in terms of prediction and control of surface settlement and gradient. Several approaches are readily used for prediction of the ground deformations associated with tunneling. There are three common approaches for estimating deformation behavior of ground and tunnel. The first involves analysis of data from laboratories and fields. The second requires the use of empirical method. The third method is the use of a more rigorous approach involving numerical analysis such as the finite element method. In recent years, numerical methods for design purposes are often used to predict deformational behavior around tunnels[1)]. Finite element procedures have been applied not only to the ground movement prediction but also to the whole tunnel design problem, which includes simulation of the construction method, analysis of the extent and development of failed zones, design of the support system, and effects on nearby tunnels, etc. In the approach of numerical modeling, those results are strongly dependent on the construction stages modeled, the constitutive law selected, and the appropriate assessment of the corresponding soil parameters. However, as many of these geotechnical finite element programs are not user-friendly, the setting up of the finite element mesh, the input data preparation, and the interpretation of the output are rather time-consuming. An alternative procedure that is useful for providing estimates of subsidence or ground deformations for preliminary design purposes is the use of an artificial intelligence technique known as artificial neural networks (ANN). This paper discusses the subsidence prediction using FEM analysis and ANN with FEM database.

This paper, firstly, investigates the application of

FEM simulation using a proposed model to predict ground movement caused by tunneling of a shallow NATM tunnel in unconsolidated soil. The proposed model used here incorporates reduction of shear stiffness, as well as strain softening effects of given material strength parameters. Numerical simulation is performed with material property values, E, ν, c, and φ, obtained from laboratory. Secondly, ANN model performs for subsidence prediction. ANN is studies the database and is trained to provide an FEM analysis result. A trained ANN model has the potential to provide accurate desired output (true output) from input data. However, once the network is trained, its running speed is very high, thereby reducting the total time consumed in the analysis. The trained ANN model was further validated by carrying out parametric studies to assess whether the model gives logical and consistent trends and a case study to verify the application to the actual NATM tunnel in prediction problem. The two methods, FEM and ANN, offer a practical way for prediction final displacement of shallow NATM tunnel, enabling rational safety management scheme to be employed.

2. APPLICATION TO THE SHALLOW NATM TUNNEL BY FEM AND ANN

(1) Nonlinear deformation in shallow tunnel

Deformational behavior around a shallow tunnel is often characterized by formation of shear bands developing from tunnel shoulder reaching, sometimes, to the ground surface. Fig.1 shows a strain distribution derived from the results of displacement measurements taken from a subway tunnel in Washington D.C.[2)]

One possible explanation of this deformational behavior may be best stated with a help of an illustration given in Fig.2. Region-A, surrounded by slip plane *k-k*, is regarded as a potentially unstable zone that may displace downward at the lack of frictional support along *k-k* planes. What is separating region-A from the surrounding is shear band *a* formed along *k-k* line with some thickness, as region A slides downward. The adjacent region-B follows the movement of region-A, leading to the formation of another shear band *b*. The direction of shear band *b* is related to 45° +φ/2 (φ: friction angle) and often coincides with what is called a boundary line of zone influenced by excavation. Regions A and B correspond to the primary and secondary zones of deformational behavior pointed out earlier by Murayama et al.[3), 4)] in the series of trap door experiments. Confirming the presence of these zones is equivalent to acknowledging formation of shear bands *a* and *b*, which may not be a desirable practice in view of minimizing deformation during construction of shallow tunnels.

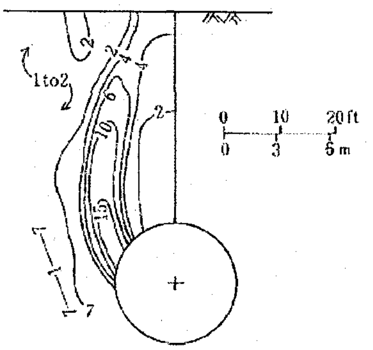

Fig.1 Strain distribution around a subway tunnel (after Hansmire and Cording, 1985[2)]).

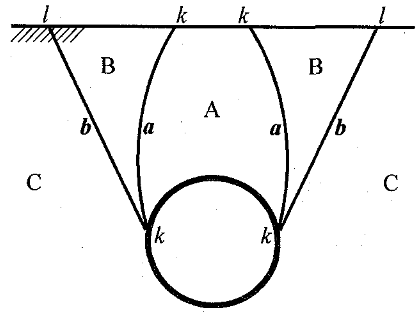

Fig.2 Typical deformational mechanism around a shallow tunnel.

However, it is regarded very important that a reliable method be established in order to reveal non-linear deformational mechanism and identify the state of deformation with reference to an ultimate state, which is of current interest in the new design practice.

(2) FEM simulation using strain softening analysis

In the framework of applying general numerical analysis tools, such as finite element methods, there have been series of approaches taken for simulation of tunnel excavation. Adachi et al.[5)] made use of classical slip line theory to define geometrical distribution of joint elements for modeling shallow tunnel excavation. Okuda et al.[6)] applied a back analysis procedure to identify the deformational mechanism, in which anisotropic damage parameter *m* was employed. Sterpi[7)] conducted strain softening analysis in which strength parameters (cohesion and friction angle) were lowered immediately after the initiation of plastic yielding. This approach was applied for the interpretation of field measurements by Gioda and Locatelli[8)] who succeeded to simulate the actual excavation procedure with accuracy. These attempts incorporate some of the key factors that must be taken into consideration for modeling shallow tunnel excavation. However, there still is shortage in modeling capability, which is expected to cope with development of shear bands, formation of primary and secondary zones, etc.

By reviewing the previous works, the authors concluded that the essential features to be taken into the numerical procedure would be reduction of shear stiffness and strength parameters after yielding (namely, strain softening)[9]. Following is a brief summary of the procedure employed in this work, as is references 10). A fundamental constitutive relation between stress σ and strain ε is defined by an elasticity matrix D

$$D=\frac{E}{1-\nu-2\nu^2}\begin{bmatrix}1-\nu & \nu & 0\\ \nu & 1-\nu & 0\\ 0 & 0 & m(1-\nu-2\nu^2)\end{bmatrix} \quad (1)$$

where $\sigma=D\varepsilon$ holds. E and ν stands for Young's modulus and Poisson's ratio, respectively. The anisotropy parameter m is defined as

$$m=m_e-(m_e-m_r)[1-Exp\{-100\alpha(\gamma-\gamma_c)\}] \quad (2)$$

where m_e is the initial value of m, m_r is the residual value, α is a constant, γ is shear strain, γ_c is the shear strain at the onset of yielding. The constitutive relationship is defined for conjugate slip plane direction (45° ±ϕ/2) and transformed back to the global coordinate system.

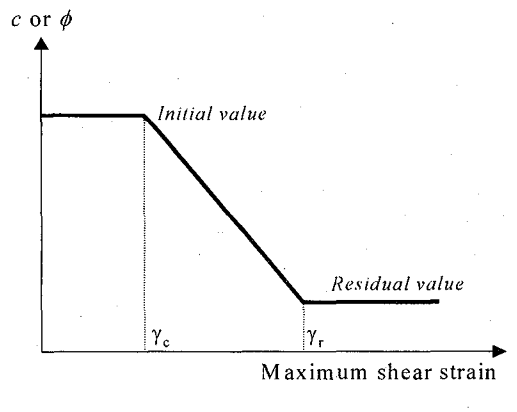

Fig.3 Reduction of strength parameters.

Strength parameters, namely cohesion c and friction angle ϕ are reduced from the moment of initiation of yielding to residual values, as indicated in Fig.3. This implies that the admissible space for stress is gradually shrunk as strain-softening process takes place. Any excess stress, which is computed on the transformed coordinate system based on slip plane direction, outside an updated failure envelope is converted into unbalanced forces that are compensated for in an iterative algorithm.

(3) Artificial neural network (ANN) analysis

ANN is a form of artificial intelligence that attempts to mimic the behavior of the human brain and nervous system. A comprehensive description of ANN is beyond the scope of this paper. Many authors have described the structure and operation of ANN[11] and its application in civil engineering [12]. A typical structure of ANN consists of a number of processing elements (PEs), or nodes, that are usually arranged in layers: and input layer, an output layer and one or more hidden layers (Fig.4).

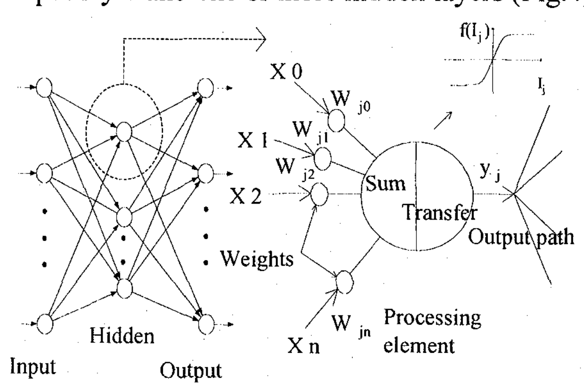

Fig.4 A typical structure of ANN

The input from each PE in the previous layer (x_i) is multiplied by an adjustable weight (w_{ji}). At each PE, the weighted input signals are summed and a threshold value (θ_j) is added. This combined input (I_j) is then passed through an non-linear transfer function ($f(I_j)$) to produce the output of the PE(y_j). The output of one PE provides the input to the PEs in the next layer. This process is illustrated in Fig.4. The network adjusts its weights on the presentation of a training data set and uses a learning rule to find a set of weights that will produce the input/output mapping that has the smallest possible error. This process is called "learning" or "training". Once the training phase of the model has been successfully accomplished, the performance of the trained model has to be validated using an independent testing dataset. As described above, ANN learns from data examples presented to them and uses these data to adjust their weights in an attempt to capture the relationship between the model input variables and the corresponding outputs. Consequently, ANN does not need any prior knowledge about the nature of the relationship between the input/output variables, which is one of the benefits that ANN has compared with empirical and statistical methods. In general, the advantages of ANN are that (1) application of the ANN does not require a prior knowledge of the process because the ANN is black-box model, (2) the ANN easily converge to the optimal solution, (3) the ANN inherently have non-linearity, (4) the ANN can have multiple inputs with difference characteristics, and (5) the ANN have the adaptability to the change of problem environment.

It has been shown that BPNN are the most popularly used ANN and they are well suited for problem of classification, prediction, adaptation control, system identification, and so on. Fig.5 illustrates typical two hidden-layer BPNN architecture used in this research because of the similarity of problem complexity to that discussed in reference 13).

The BPNN always consists of at least three layers; input layer, hidden layer and output layer. Each layer consists of a number of elementary processing units, called neurons, and each neuron is connected to the next layer through weights, i.e. neurons in the input layer will send its output as input for neurons in the hidden layer and similar is the connection between hidden and output layer. Number of hidden layer and number of neurons in the hidden layer is changed according to the problem to be solved. To differentiate between the different processing units, values called biases are introduced in the transfer functions.

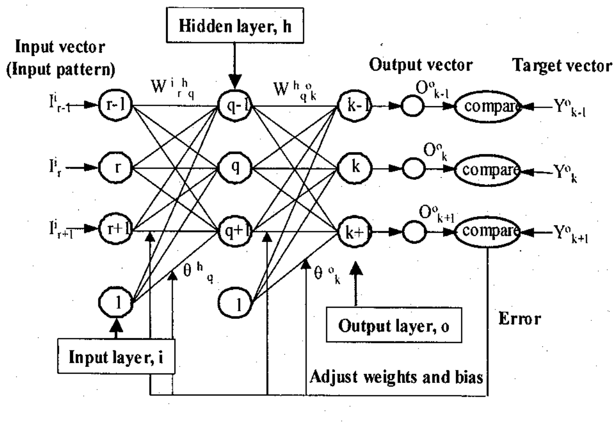

Fig.5. Scheme of Three-layered BPNN

These biases are referred to as the temperature of a neuron. All neurons in the BPNN are associated with a bias neuron and a transfer function, except for the input layer. The bias has a constant input of 1, while the transfer function filters the summed signals received from this neuron. The application of these transfer functions depends on the purpose of the neural network. The output layer produces the calculated output vectors corresponding to the solution. During training of the network, data is

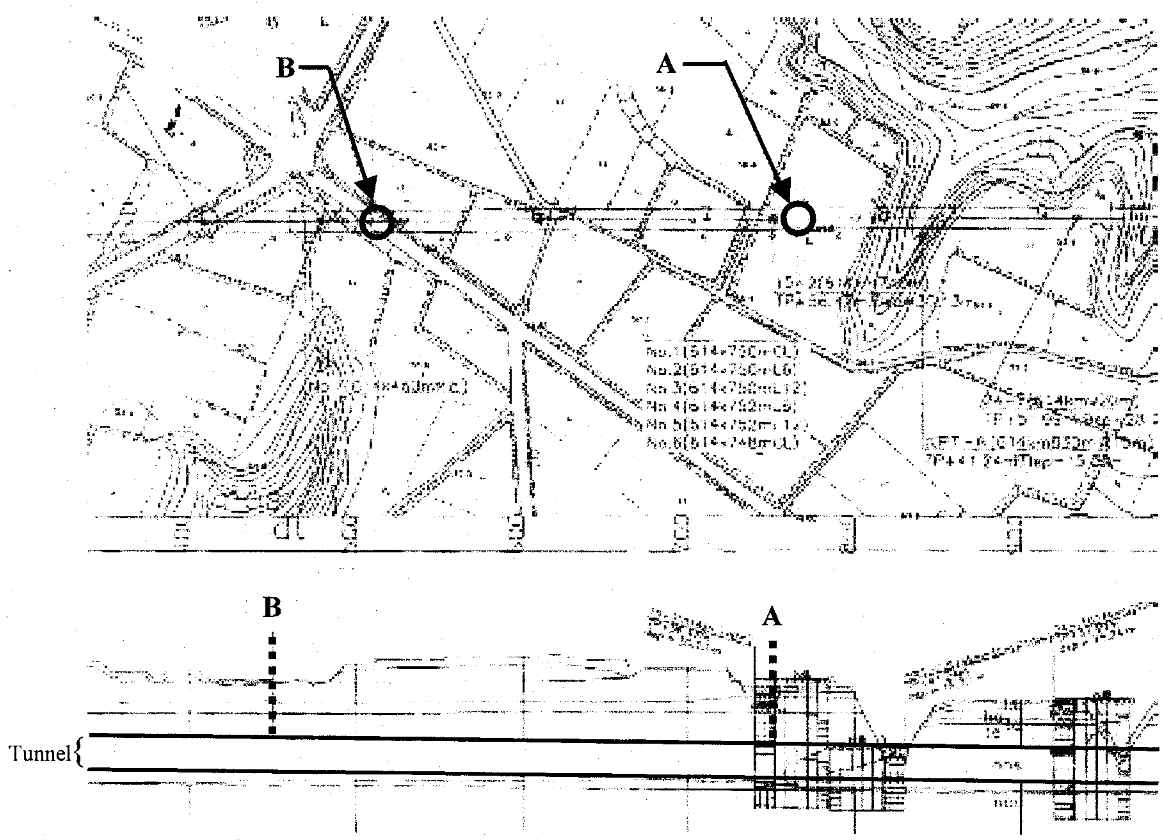

Fig.6 Plan and vertical view of the site. Monitored sections are indicated as **A** and **B**.

processed through the input layer to hidden layer, until it reaches the output layer, as is called forward process. In this layer, the output is compared to the targeted values (the "true" output). The difference or error between both is processed back through the network, as is called backward process, updating the individual weights of the connections and the biases of the individual neurons. The input and output data are mostly represented as vectors called training pairs. The process as mentioned above is repeated for all the training pairs in the dataset, until the network error converged to a threshold minimum defined by a corresponding sum square error function.

Tab.1 Material properties for 4 layers.

	Takadate volcanic layer 1	Takadate volcanic layer 2	Noheji sandy layer 3	Noheji sandy layer 4
$r(kN\ m^3)$	14	18	20	20
E(Mpa)	5	5	80	100
ν	0.286	0.286	0.286	0.286
ϕ	0	0	35	35
c(Mpa)	30	45	30	50

3. DEFORMATION ANALYSIS BY FEM

(1) Construction site for Rokunohe tunnel

The Rokunohe tunnel, 3810m long, is located at the northern end of the Honshu, between Hachinohe and Shin-Aomori as shown in Fig.6. The excavation was conducted by top heading method. Excavation of the lower section excavation followed approximately 40m behind the face of the upper section excavation. Reinforcement of supports has been put by using rockbolt, shotctete and steel support as shown in Fig.7.

Auxiliary method is applied by face shotcrete, face bolt, deep well, well point, and so on, for face stabilization and water inflow control.

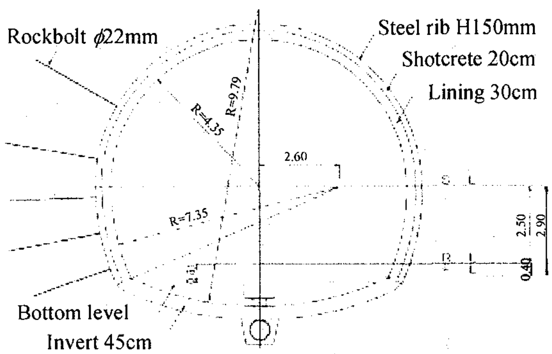

Fig.7 Tunnel cross section.

The geological profile of the ground consists of unconsolidated sand layer (Layer 3) which is lying beneath two layers (Layers 1 and 2) of volcanic ash. The material properties obtained for each layer are shown in Tab.1. During the tunnel construction, various measurements on tunnel and ground were carried out to confirm the stability of the tunnel and the adequateness of the excavation method. Crown settlement, convergence, surface settlement, subsurface settlement and horizontal displacement were measured as shown in Fig.8.

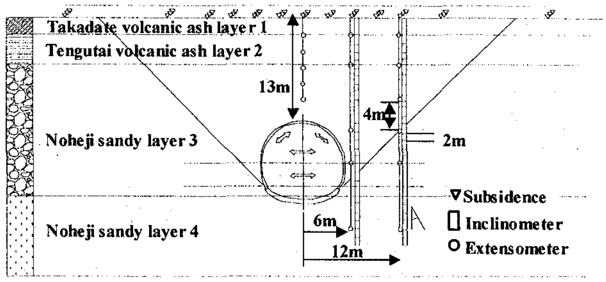

Fig.8 Field instrumentation.

(2) Outline of numerical simulation

Numerical simulations were conducted for two cross sections with slightly different geometric configuration. Locations for the two sections A and B are shown in Fig.6. Geometry and boundary conditions of the finite element meshes are shown in Fig.9 for the case of Section A. The ground behavior was modeled with three different constitutive laws; namely 1) an elastic model, 2) elastic-plastic material model with a Mohr-Coulomb failure criterion and 3) the strain softening model[9]. Shotcrete and steel support were modeled as elastic elements. Rock bolts are not modeled in this analysis. The construction sequence is to excavate the top heading (upper section) in advance followed by bench (lower section) and invert excavation. Simulation has been performed in several computational steps for excavation of the tunnel top heading.

In the first step, 40% stress release ratio with excavation of the top heading (upper section) has applied. This step relates to the timing when an upper section arrives at a tunnel face. In the second step, the support has been put in place and, at the same time, the remaining 60% of the excavation forces was released.

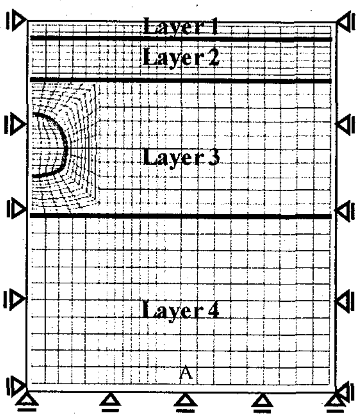

Fig.9 Finite element mesh used for simulation.

The same approach was taken for excavation of lower half and invert portion. As for strain softening analysis, parametric study was performed in which $\Delta\gamma$ (increment of maximum strain during which strength drops from peak to residual value, see Fig.3 and the ratio of residual to original strength, for example c_r/c_i where c_r and c_i are residual and initial cohesion values, were varied, resulting in the total of 9 cases as shown in Tab.2.

Tab.2 Scheme for strain softening analyses.

		Residual strength/Original strength		
		80%	60%	40%
	0.04	Case 1	Case 4	Case 7
$\Delta\gamma$	0.02	Case 2	Case 5	Case 8
	0.01	Case 3	Case 6	Case 9

(3) Numerical result

Fig.10 shows surface subsidence from 3 different material models and the measurement defined for the final stage. As for the results of strain softening analysis, the one which gave the closest results to the measurement is shown for both cross sections A and B. For section A, where the maximum subsidence was around 10mm, the results from different models show insignificant differences. Although there is some discrepancy in the gradient of subsidence, however, this is regarded acceptable because the absolute values of displacement and its gradient are very small. On the contrary, those for section B, where the displacement in excess of 50mm was measured; the superiority of the softening model is seen as compared to elastic or elasto-plastic analysis. A clear advantage of the strain softening analysis is seen here for section B, where the shear band development might have occurred to produce this particular profile of surface subsidence.

Finally, Fig.11 shows the maximum shear strain distribution at the final stage of analysis for sections A and B. It is seen for section A, all material models resulted in similar images since the magnitude of displacement here was constrained to fairly low level. However, for section B, the case which showed the best results in comparison with the measurement, namely the result from the softening analysis, shows the development of shear band from tunnel shoulder. The band is believed to be of a fair size, although it has not reached the surface of the ground. However, this development of the shear band is regarded as the cause of large displacement that occurred for this section.

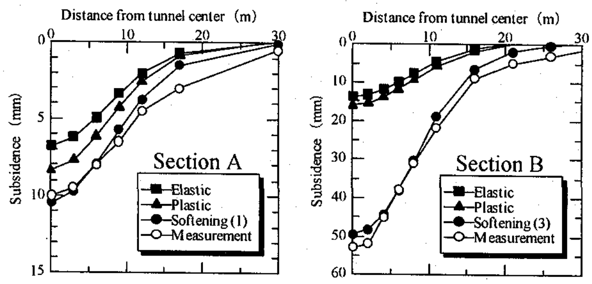

Fig.10 Surface subsidence at final stage. (Softening (1) and (3) in legends relate to analysis cases, Case 1 and Case 3, respectively)

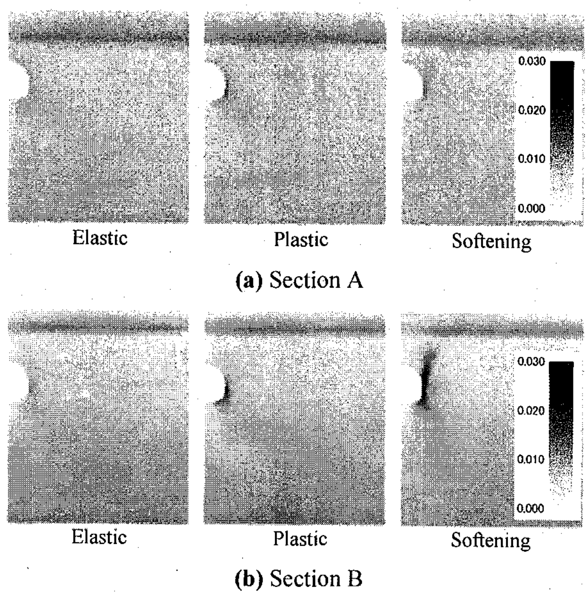

Fig.11 Maximum shear strain distribution at final stage.

4. ANN MODEL DEVELOPMENT

(1) FEM database

Fig. 12 shows a schematic representation of the excavation geometry and the main parameters considered in the analyses. A total of 32 governing parameters were used as the input variables for the neural network model. The output variable was the subsidence point, S_n where n denotes distance from center,, as shown in Fig. 12. Fig. 12 shows the scheme of output variable. A total of four soil layers (soil types) were considered as depicted in Fig. 12. For each soil layer, the required input parameters are the unit weight of the soil γ, the initial Young's modulus E, the horizontal stress state K_0, the cohesion c, the friction angle ϕ, the increment of maximum strain during which strength drops from peak to residual value $\Delta\gamma$ and the ratio of residual to original strength β and the thickness of the soil layer t.

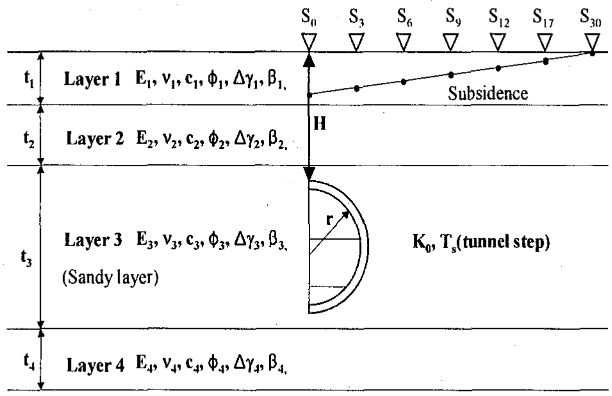

Fig. 12 Cross-section of NATM tunnel geometry

The other input variables for the model are the excavation radius r, the excavation depth H and tunnel excavation step T_s. The FE program used strain softening model, for learning and testing data sets. With varying parameter properties range, FEM is performed and its result arranged as database for ANN input/output used. FEM analyses to create ANN database were performed using property values given in Table 3.

The data obtained from the FE analyses were randomly separated into 1134 learning patterns and 196 testing patterns.

Tab. 3 Parameter properties for FEM database

Selected parameter	E(Mpa)	K_0	$\Delta\gamma$	β
Properties range	80,160,240	0.4,0.5,0.6,0.7,0.8,0.9,1.0	0.01, 0.02, 0.04	80%,60%, 40%

(2) Model input/output structure and data pre-processing

The ANN maps input vectors onto output vectors. It can be trained to map given input vectors onto respective given output vectors referred to as desired output vector. Fig.13 shows the ANN structure for subsidence prediction. Learned ANN model has the potential to provide accurate desired parameter properties (output) from measurement data (input).

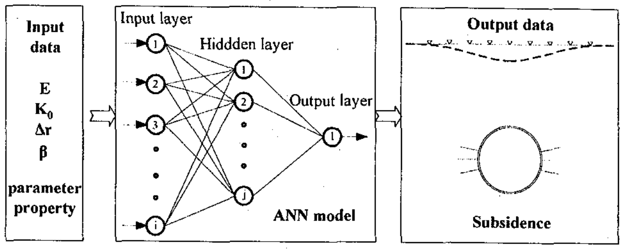

Fig.13. ANN model structures

After input/output data division, it is important to pre-process the data to a suitable form before they are applied to the ANN. Pre-processing the data, such as scaling, is important to ensure that all variables receive equal attention during training.

(3) BPNN development process

The sigmoid function is preferred as the transfer function in this study and is used the delta rule for the learning rule of BPNN. The validation of a trained ANN model is based upon one or more error indices, such as mean absolute error (MAE), mean square error (MSE), and root mean square error(RMSE). The RMSE was used in the paper for the evaluation of the ANN performance. In this paper, training parameter is used as a tolerance to indicate end of training that the number of training (Epoch) over 400000 or the error of the network (SSE) is below 0.0001. The initial weight range was selected as [0.5;0.5]. In this study, the learning rate was selected as 0.01, 0.1 and 0.3 separately for the training process to search for the most effective ANN architecture; the momentum coefficient was also selected as 0.1,0.3,0.5,0.7 and 0.9. In order to obtain good performance of the ANN, tuning of the ANN architecture and parameters is indispensable. In this case, the ANN architecture was tested with various nodes per hidden layer and the ANN parameters with various learning rate and momentum rates to find fine better values and architecture. ANN analysis process is follow as;

①Section of data preparation and pre-processing.

② Define the neural network structure and parameter about the given problem.

③Next, the neural network is trained by using the input and output data of learning process.

④To confirm awareness ability of neural network that finishes studying, we achieved the testing(prediction) by using data which are not used for learning. Network development was performed on an IBM-compatible Pentium 4 class machine

(598MHz, 248MB RAM). Training took about 4-hours for 600 thousand training cycles.

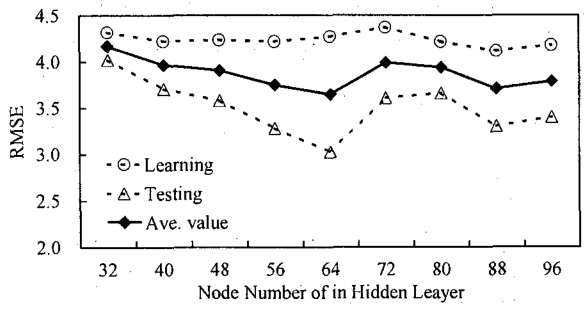

Fig.14 ANN output for different hidden layers

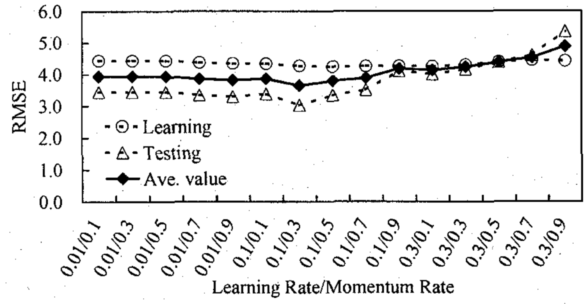

Fig.15 ANN output for different learning rate , α, and momentum rate,ξ.

(4) BPNN results

The development of an ANN model for subsidence estimation during tunneling was performed for cross section A. In order to obtain good performance of the ANN, the ANN architecture was tested with various number of node per hidden layer, various learning rates and momentum rates. Firstly, the influenced of the pattern analysis with various ANN structure and parameter was studied. The RMSE was used in the paper for the evaluation of the ANN performance. Despite learning data being adequately prepared, it is known that predictability of an ANN varies depending on the chosen architecture and learning environments. In addition, ANN learning should be carefully carried out to guarantee generality for further application. Therefore, following the trial-error method, it was recommended to choose an optimal architecture of ANN, as well as adapted learning parameters, for a given learning pattern. To confine the generality of a trained ANN, testing is undertaken with un-used 13 data sets. The ANN outputs are shown in Figs. 14 and 15.

Fig. 14 show the ANN output for different hidden node with RMSE in $\alpha = 0.1$ and $\xi = 0.3$. The result revealed that the BPNN model had a better learning and testing at the 64 nodes and RMSE value was 3.02 for the subsidence estimation. Fig. 15 show the ANN output for different ANN parameter with Ave. RMSE in hidden node=64. The result showed that the learning and momentum rate were 0.1 and 0.3 that had a better learning and testing and RMSE value were 3.02. In Fig. 14 and 15, Ave. RMSE means the average of total RMSE value of learning and testing time.

Tab. 4 shows ANN structure pattern for optimal structure determination in subsidence prediction. ANN architecture, 32-64-7, shows that input layer unit is 32, hidden layer unit is 64 and output layer is 7. And, output layer, 7, is subsidence point, as in Fig.12. Fig.16 show the comparison of true output (target data) and calculated ones in subsidence point, S_0.

Tab. 4 Learning and testing result of ANN

BPNN model	A section	B section
Learning data/Testing data	1134/168	1134/216
Learning rule	Delta rule	Delta rule
Transformation function	Sigmoid	Sigmoid
BPNN structure	32-64-7	25-25-10
Learning rate	0.1	0.1
Momentum rate	0.3	0.7
Fianl system error	0.79	1.13
Final epoch(cycles)	2793	1378
Learning Ave. RMSE	4.27	3.51
Testing Ave. RMSE	3.02	1.93
Learning Ave. R2	0.97	0.97
Testing Ave. R2	0.95	0.94

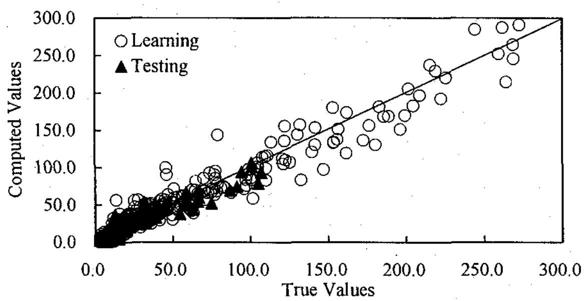

Fig.16 True value vs. computed value by ANNs,S_0

The correlation coefficient for the training and testing are 0.96. The results indicate that the model is able to capture the relationship between the inputs (material parameter and tunnel dimension and soil condition) and outputs (subsidence).

5. SUBSIDENCE ANALYSIS BY ANN

5.1 Subsidence prediction

As mentioned earlier, this neural network model has the advantage over other more conventional methods in that once learning (weight adjustments) is completed, it provides rapid results. In A cross-section, Fig.17 shows plots of the finite element method (FEM) subsidence values versus the values predicted by the neural network (NN), with field data. In Fig.17, this shows little difference between FEM, ANN result and field measurement. From its result, the neural network model analyses agree with FEM result and measured data. That is, ANN analysis can provide prediction value of subsidence behavior during tunneling in a much faster way than by other method. However, if we make sure of adequate stress-strain model and reliable measurements data, proposed method will assist the NATM tunnel design/construction in view of parameter estimation and prediction of ground movement.

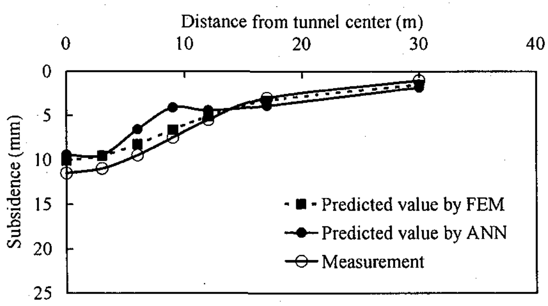

Fig.17 FEM values versus the predicted by the neural network.

(2) Further validations; Key parametric studies using trained ANN model

Key parametric studies using trained ANN model was performed to assess whether the model gives logical and consistent trends. It should be noted that these analyses were carried out using another independent set of FE generated data that are different from the training and testing data described earlier. In Fig.18 and 19, the effects of $\Delta\gamma$ value of sandy layer were examined. Fig. 18 shows the effect of the Young's modulus, E, on the maximum surface settlement.

The general trend was for the maximum surface settlement to decrease with increasing Young's modulus and increasing $\Delta\gamma$ values. As expected, the settlements tend to decrease. The plot in Fig. 19 showed the same trend of maximum surface settlement decreasing with increasing residual strength/original strength and $\Delta\gamma$ values. Generally, the above results demonstrate that the trained neural network model gave reasonable and consistent relationships between the various input variables.

Parametric studies using the trained network model can be readily performed as illustrated in this section. The trained network model is not only able to capture the non-linear relationship of the input variables but also their inter-dependency. This is mainly due to its inter-connective architecture of the neural network model.

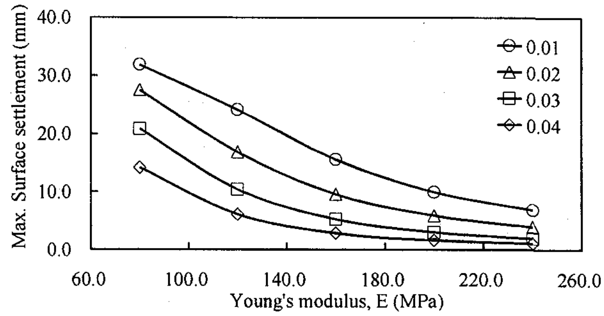

Fig.18 Plot of maximum surface settlement versus Young's modulus with $\Delta\gamma$=0.01, 0.02, 0.03 and 0.04.

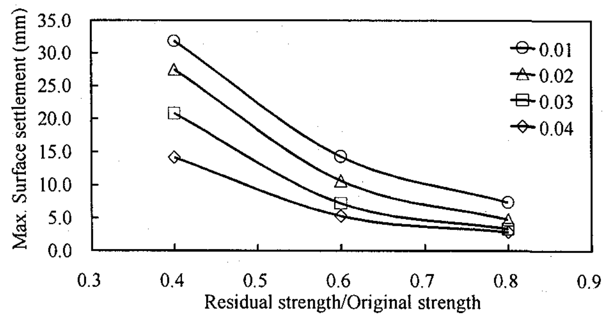

Fig.19 Plot of maximum surface settlement versus residual strength/original strength with $\Delta\gamma$=0.01, 0.02, 0.03 and 0.04.

6. CONCLUSION

This paper discussed the subsidence prediction using artificial neural network (ANN) and FEM database. The ground movement was predicted using FEM analysis and ANN ones. A case study was performed to verify the application to the actual NATM tunnel. Once the network is trained, its running speed is very high, thereby reducing the total time consumed in the analysis which is conducted once construction starts. As a nonlinear problem such as shallow tunneling problems contains inherent complexity in a model set up whether that is for a FEM modeling or a ANN modeling. It is, however, advantageous to employ the ANN approach and execute pre-computation, namely structuring of the ANN model, before construction. This enables fast analysis of the measured deformation leading to quick engineering judgment, if necessary, regarding safety issues on site.

REFERENCES

1) Negro,A. and de Queiroz,P.I.B. : Predictin and performance:A review of numerical analyses for tunnels, *Geotechnical Aspects of Underground Construction in Soft Ground*, edited by Fujita and Miyazaki, pp.409-418, 2000.
2) Hansmire,W.H. and Cording,E.J. : Soil tunnel test section; Case history summary, *Journal of Geotechnical Engineering*, ASCE, Vol.111, No.11, pp.1301-1320, 1985.
3) Murayama, S. and Matsuoka, H. : On the settlement of granular media caused by the local yielding in the media, *Proceedings of JSCE*, Vol.172, pp.31-41, 1969. (*in Japanese*)
4) Murayama, S. and Matsuoka, H. : Earth pressure on tunnels in sandy ground, *Proceedings of the JSCE*, Vol.187, pp.95-108, 1971. (*in Japanese*)
5)Adachi, T., Tamura, T. and Yashima, A. : Behavior and simulation of sandy ground tunnel, *Proceedings of the JSCE*, 358(III-3), pp.129-136, 1985. (*in Japanese*)
6) Okuda, M., Abe, T. and Sakurai, S. : Nonlinear analysis of a shallow tunnel, *Journal of Geotechnical Engineering*, JSCE, 638(III-49): pp.383-388, 1999. (*in Japanese*)
7) Sterpi, D.: An analysis of geotechnical problems involving strain softening effects, *International Journal for Numerical and Analytical Methods in Geomechanics*, Vol.23, pp.1427-1454, 1999.
8) Gioda, G. & Locatelli, L. : Back analysis of the measurements performed during the excavation of a shallow tunnel in sand, *International Journal for Numerical and Analytical Methods in Geomechanics*, Vol. 23, pp.1407-1425, 1999.
9)Akutagawa,S., Kitani,T. and Matsumoto,S. : Numerical modeling of a nonlinear deformational behavior of a tunnel with shallow depth, Proceedings of the Int. Symp. of Modern tunneling Science and Technogy, Vol.1, pp. 111-114, edited by Adachi et al., 2001.
10) Matsumoto, K. : Fundamental investigation on design pressure of tunnels, Masters thesis, Graduate School of Science and Technology, Kobe University, 2000.
11) Hecht-Nielsen, R. : Neurocomputing. Addison-Wesley, Reading, MA., 1990.
12) Flood,I. and Kartam,N. Neural networks in Civil Engineering. I: Principles and understanding, *Journal of Computing in Civil Engineering*, ASCE, Vol.8, No.2, pp.131-148, 1994.
13) Kim,T. and Valdés,J.B. : Nonlinear model for drought forecasting based on conjunction of wavelet rransforms and neural networks, *Journal of Hydrologic Engineering*, ASCE, Vol.5, pp.319-328, 2003.