인공신경망과 수치해석을 이용한 NATM터널의 비선형 거동 분석
Non-Linear Deformation Analysis of NATM Tunnel using Artificial Neural Network and Computational Methods

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개요(SYNOPSIS) : 도심지 터널의 설계, 시공 그리고 유지관리에 있어서 지반 변위 억제와 변형거동 예측은 중요하다. 국내·외 연구자들은 다양한 수치해석적인 기법과 현장 계측 결과를 이용하여 터널 시공과 관련된 변형거동 예측을 시도하였다. 하지만, 설계물성치의 산정과 지반 모델링 그리고 수치해석기법과 관련된 사용상의 어려움에 의해 아직까지 만족스러운 결과를 얻지는 못하였다. 본 논문은 수치해석적인 기법과 인공신경망을 이용하여 도심지 NATM 터널의 설계 물성치 산정과 변형거동 예측에 관한 방법을 제안하였다. 인공신경망 모델 개발을 위한 학습과 테스트과정은 데이터베이스된 수치해석결과를 이용하였다. 개발된 인공신경망 모델은 입력변수인 지반변위와 결과변수인 설계 물성치 간의 상호관계를 적절히 인식할 수 있다. 수치해석은 지반의 연화거동을 모사할 수 있는 변형률 연화모델을 적용하였다. 사례분석에 있어서 굴착 초기단계의 계측 값을 개발된 인공신경망 모델에 입력하여 설계 물성치를 계산하였으며, 수정된 설계 물성치는 수치해석을 통하여 다음 굴착단계에서의 터널 주변의 지반 변형거동을 예측하였다. 본 논문에서 제안된 방법을 토대로 시공조건이 엄밀한 도심지 터널의 설계물성치의 정량적인 평가 및 변형거동 예측이 계측이 입수된 초기 굴착단계에서 가능할 것으로 기대된다.

주요어(Key words) : NATM 터널, 유한요소해석, 인공신경망, 설계 물성치 산정, 변형거동 예측

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). Numerical simulation tools, such as Finite Element Method (FEM), have been and are indispensable tool for tunnel engineers for many years. It is, however, a commonly acknowledged fact that determination of input parameters, especially material properties exhibiting nonlinear stress-strain relationship, is not an easy task even for an experienced engineer. Use of measured displacement for parameter determination has been researched over the years, and one geotechnical engineering principle has been formed as back analysis (Sakurai and Takeuchi, 1983; Gioda and Sakurai, 1987). However, there still is fundamental difficulty in parameter identification problems when ground materials exhibit nonlinear behavior of deformation. One possible approach to overcome this problem is to use Artificial Neural Networks (ANN) with FEM database that have recently been applied to some geotechnial problems (Deng and Lee, 2001; Pichler et al., 1978; Yoo and Kim, 2007).

This paper firstly introduces a brief framework of an ANN approach. The proposed approach is then described with reference to a parameter determination problem for a NATM tunnel in two stages. It is shown that by building appropriate database and ANN models beforehand, an immediate processing of field measurement results become possible, that also enables prediction of displacements around tunnel for final stage while construction process is still midway.

2. ANN approach for design parameter determination with FEM database

In order to define key timings in typical tunnel construction, Fig. 1 is shown to depict the relationship between displacement and time with respect to construction sequences. Tunnel cross section is assumed to be excavated in three stages; namely, excavation of top heading, bottom heading and invert. With regard to the timings of performing back analysis, T_2 (the timing of top heading face arrival) is regarded as a first key epoch and indicated as Action timing 1 in the figure. Generally speaking, this stage is regarded as a fairly early stage and deformation process is most likely elastic. Therefore, two most influential parameters controlling elastic deformation; namely Young's modulus E and horizontal stress ratio K_0, are identified from measured displacements. The second key timing is set to T_4 indicated as Action timing 2 in the figure. By this time, the top heading excavation is finished and some signs of nonlinear deformation process are generally present. Therefore, measured displacements at this stage are used to identify two parameters controlling nonlinear deformation; namely strength reduction factor β and strain increment $\Delta\gamma$ during which strength drops from original to residual values. Determination of these 4 parameters leads to complete description of ground material, therefore one can perform predictive nonlinear analysis to simulate all remaining stages of excavations defining ΔU_B and ΔU_I and assuring safety throughout the excavation processes.

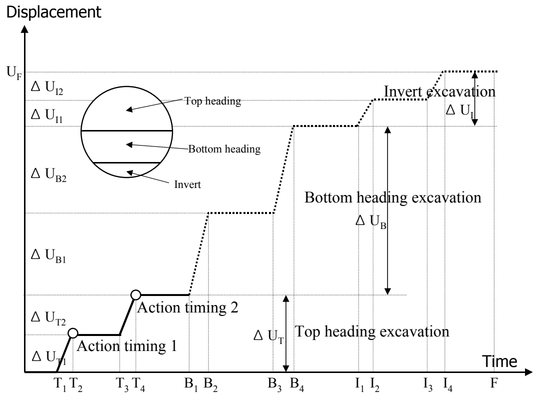
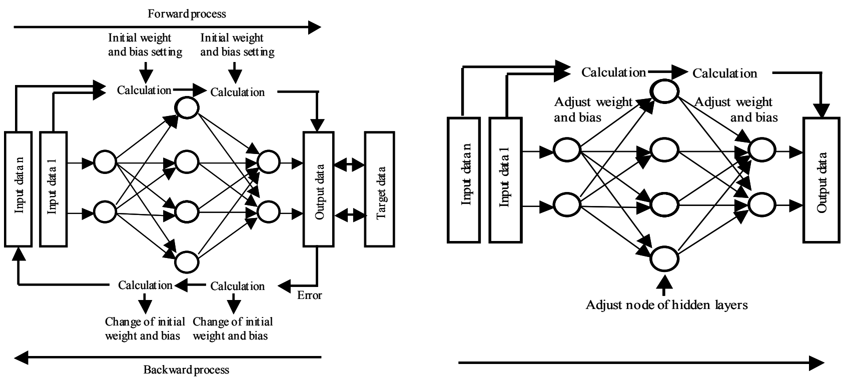


Fig. 1 Displacement versus time relationship with respect to construction stages.

3. Outline of Artificial Neural Network

The human nervous system consists of billions of neurons of various types and lengths relevant to their location in the body (Schakoff, 1997). Back Propagation Neural Network (BPNN) is the most popularly used ANN and it is well suited for problem of classification, prediction, adaptation control, system identification, and so on (Rumelhart et al., 1995; Baheer, 2000). 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. The output layer produces the calculated output vectors corresponding to the solution. BPNN performs in two phases; learning (training) phase and testing (or validation) phase. During learning of the network, as in Fig. 2 (a), data is 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. A network could provide almost perfect answers to the set of problems with which it was trained, but fail to produce meaningful answers to other examples. Validation involves evaluating the network performance on a set of test problems that were used for training, but for which solutions are available for comparison. Testing phase is a calculation process that is undertaken after training has been completed, as shown in Fig. 2 (b). In order to perform a BPNN analysis, one needs to be aware of several parameters and operations associated with network training (Hagazy et al., 1994). They are database size and partitioning, data preprocessing, balancing, data normalization, input/output representation, network weight initialization, BPNN learning rate and momentum coefficient, transfer function, convergence criteria, number of training cycles, training modes, hidden layer size and parameter optimization so on (Baheer, 2000).



(a) Learning phase (b) Test phase

Fig. 2 Learning and testing phase in neural network system

4. FEM analysis in studied tunnel site

4.1 Studied tunnel site

Development of ANN models for parameter identification was performed for the Rokunohe tunnel in part of the TOHOKU SHINKANSEN project in Japan. The Rokunohe tunnel, 3810m long, is located between Hachinohe and Shin-Aomori at the northern end of Honshu island. Fig. 7 shows the studied tunnel cross section B, and its measurement plan. In Section B, surface settlement and subsidence settlement were measured as shown in Fig. 3. In Fig. 3, we found that the studied tunnel is located in an unconsolidated sand layer (indicated as Nos). The geological profile of the ground consists of unconsolidated sand layer (Nos) in excess of 30m, which is lying beneath two layers of volcanic ash. Bench excavation followed approximately 40m behind the face of the top heading excavation. Fig. 4 shows the typical cross section of the tunnel. Tunnel supports have been put in by using rockbolt, shotctete and steel ribs. The tunnel will cross under public facilities such as roads, railways, water channels for agriculture.

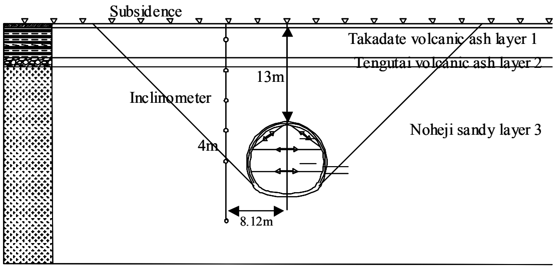


Fig. 3 Studied tunnel cross section and measurement plan

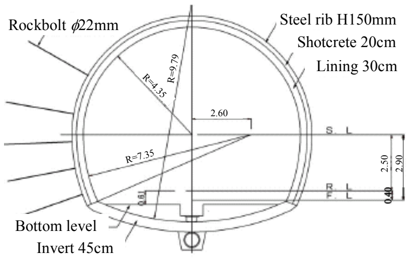


Fig. 4 Tunnel cross section.

4.2 Strain soften modeling

Matsumoto(2000) showed the shear band developing with excavation procedure by a strain softening model and its results compared with model tunnel test. This strain softening model employed in this study incorporates the reduction of shear stiffness (Sakurai and Akayuli, 1998), m ($=G/E$), as well as strain softening effects; namely, reduction of strength parameters c and ϕ during strain increment after yielding. A fundamental constitutive relation between stress, σ', and strain,ε', is defined by equations (1) and (2) defined for a local coordinate system(Akutagawa et al., 2006).

$$[\sigma'] = [D'][\epsilon'] \qquad (1)$$

$$[D'] = \frac{E}{1-v-2v^2}\begin{bmatrix} 1-v & v & 0 \\ v & 1-v & 0 \\ 0 & 0 & m(1-v-2v^2) \end{bmatrix} \qquad (2)$$

An anisotropic parameter m is defined to be the ratio of G to E and expressed as, $m=G/E$, when there is no damage yet. Once damage starts to develop within material, m can be defined using the damage parameter d as $m=1/(2(1+\nu)-d$. Poisson's ratio, ν, is assumed to be constant. The damage parameter, d, can be expressed as a function of shear strain defined for a local coordinate system for a slip plane as;

$$d = (m_e - m_r)[1-\exp\{-100\alpha(r-r_e)\}] \qquad (3)$$

where m_e is the initial value of m, m_r is the residual value, a is a constant, γ is shear strain, γ_e is the shear strain at the onset of yielding. m is lowered immediately after the initiation of plastic yielding (Sakurai and Akyayuli, 1998), reaching finally to its residual value. The constitutive relationship is defined for conjugate slip plane directions ($45^0 \pm \phi/2$) and transformed back to the global coordinate system. Eq. (2) can be transformed to global coordinates as follows:

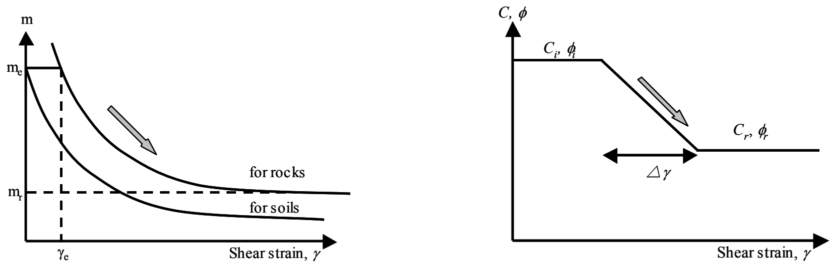
$$[D] = [T][D'][T]^T \qquad (4)$$

where, *[T]* is a transformation matrix. The stress strain relationship for the global coordinate system is given in the following form:

$$[\sigma]=[D][\epsilon] \qquad (5)$$

$$[D]=\frac{E}{1-v-2v^2}\begin{bmatrix}1-v & v & 0\\ v & 1-v & 0\\ 0 & 0 & (1-2v)/2\end{bmatrix} \qquad (6)$$

When damage has not occurred, the relation m=1/2(1+ν) holds, and matrix *[D']* is identical to *[D]*. The proposed numerical analysis incorporates the strain-induced reduction of shear stiffness as well as strain softening effects, as indicated in Fig. 5.



(a) Reduction of shear stiffness, *m* (b) Softening effect of strength parameter
Fig. 5 Concept of strain softening modeling

4.3 FEM mesh and numerical analysis results

Geometry and boundary conditions of the finite element meshes of sections B are shown in Fig. 6. The ground behavior was simulated with the strain softening model proposed in this paper. Shotcrete and steel support were modeled as elastic elements. Simulation has been performed in several computational steps for excavation of the tunnel top heading in advance followed by bench (lower section) and invert excavation. Standard horizontal stress ratio, K_0, was calculated by $\nu/(1-\nu)$, where ν is Poisson's ratio. Eight-node iso-parameteric plane strain element is used to model soil. Lee et al. (2005) has report that the application of strain softening analysis to predict the deformation behavior around ground in this studied tunnel cross section B. They represented that the strain softening analysis results produced a surface settlement profile and ground displacement, which are in good agreement the measured field data, as shown in Fig. 7.

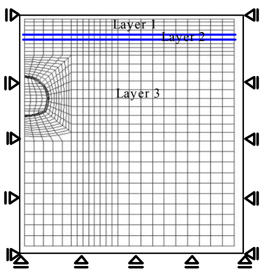


Fig. 6 Finite element meshes

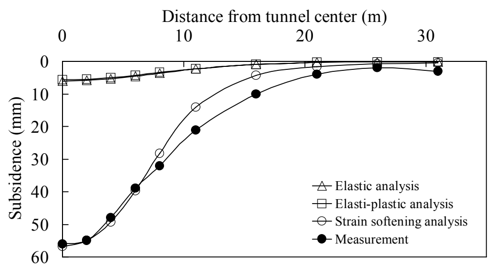


Fig. 7 Comparison between measured value and calculated ones

These parameters selected by repetitive updated process, as parameter tuning. However, disadvantageous in terms of time required for re-computation of displacement everytime new data come in.

5. Determination of design material properties for strain soften modeling

5.1 Proposed ANN system

Fig. 8 shows a flow of the procedure proposed in this paper. Two different timings, T_2 and T_4, are set for setting up ANNs for respective purposes, as described before. Firstly at T_2, key parameters are Young's modulus E and horizontal stress ratio K_0. An ANN model set up is possible such that measured displacements are input into the model, and E, K_0 are output simultaneously. That is that the first ANN, Model-1, is set up such that measured displacement are input to define E only (Fig. 9(a)). The second ANN, Model-2, also uses the same measured displacement and the newly determined E as input data to define K_0 (Fig. 9(b)). These two models, Model-1 and Model-2 are defined at T_2, the arrival of top heading face. A similar two-step approach is also employed at the second timing, T_4, which is defined at the completion of the top heading excavation. Model-3 (Fig. 9(c)) uses measured displacements, E and K_0 as input, to determine β which indicates ratio of dropped cohesion and friction angle to their original values.

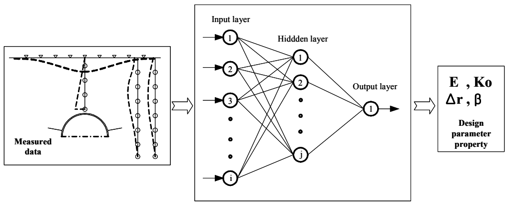
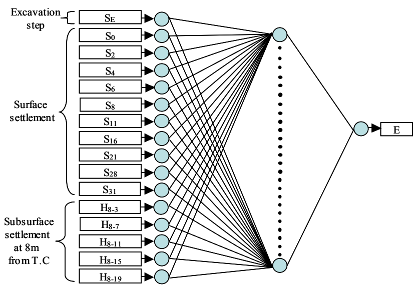
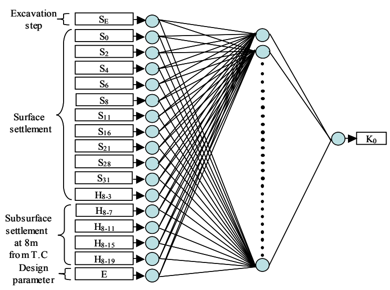


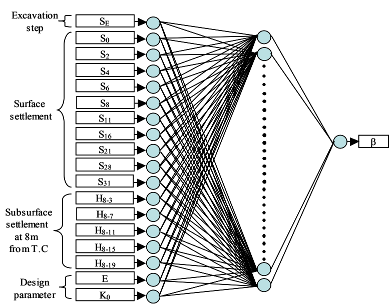
Fig. 8 A scheme of the proposed ANN model



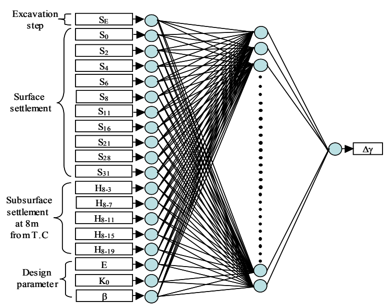
(a) Model-1 for E



(b) Model-1 for K_0



(c) Model-1 for β



(d) Model-1 for Δr

Fig. 9 The structure of ANN model used for parameter identification in section B

The last ANN model, Model-4, uses the measured displacement, E, K_0 and β, to define the last key parameter which indicates strain increment during Δr, which strength parameters drop from original to residual values, as shown in Fig. 9 (d). By this strategy, two key parameters controlling elastic behavior of the ground can be determined at the arrival of top heading face, T_2. Other two parameters controlling nonlinear behavior can be determined when the top heading excavation is completed, T_4.

5.2 Building database using numerical tool and data division

There could be several possible form of database from which a rational relationship between input parameters (displacement measured during tunneling) and output parameters (linear and nonlinear material properties) is to be built. For database generation by parametric FEM analyses, the reasonable ranges of material parameter values, E, K_0, β and Δr, values were important. These parameters are difficult to determine by laboratory and field test. Parametric FEM analysis for ANN database carried out considering above mentioned reference, as Lee et al.(2005). Table 1 shows the materials properties used for FEM database and its database values used for ANN learning process. In Table 1, those parameters for which multiple variations were employed and shown by gray hatch. For example, three different values, namely 80, 60 and 40%, were used forβ. The ration m_r/m_i was assumed to be the same as β. Like wise, parameters Δr, E and K_0 had 3, 3 and 7 different values. All possible combination of these variables led to 189 patterns (3×3×3×7) of analyses to become elements in the database. It is a common practice to divide available data into two subsets; training set to construct a neural network model, and an independent testing set to estimate model performance in the deployed environment. Recent studies have found that the way of dividing the data can have a significant impact on the results (Takar and Johnson, 1999). To develop the best possible model, which gave the available data, all patterns are contained in the data, which are needed to be included in the training set. Similarly, since the test set is used to determine when to stop training, it needs to be representative of the training set which should also contain all of the patterns that are present in the available data. In order to achieve this, FEM analysis for the testing data sets were prepared in Table 2, which material properties based on sand (Nos.) layers in section B. Testing material properties were considered above comment, as the same population in training and testing data set.

Table 1. Parameter values used FEM database

Tunnel section		Section B		
Type of ground layer		Layer 1	Layer 2	Layer 3
		Takadate volcanic ash	Tengutai volcanic ash	Noheji sandy
Material paramters	r (kN/m^3)	14	18	20
	E (MPa)	5, 10, 15	5, 10, 15	80, 160, 240
		0.286	0.286	0.286
		30	45	30
	c (MPa)	0	0	35
		40, 60, 80		
	Δ	0.01, 0.02, 0.04		
Horizotal stress ratio	K_0	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0		
Support paramter	E (MPa)	5000		

; Selected value for parameter study

Table 2. An example of parameter value used testing

Tunnel section		Section B		
Type of ground layer		Layer 1	Layer 2	Layer 3
		Takadate volcanic ash	Tengutai volcanic ash	Noheji sandy
Material paramters	r (kN/m^3)	14	18	20
	E (MPa)	11.25	11.25	180
	□	0.286	0.286	0.286
	□□↑□	30	45	30
	c (MPa)	0	0	35
	□□↑ →	80		
	Δ □	0.04		
Horizotal stress ratio	K_0	0.6		
Support paramter	E (MPa)	5000		

5.3 Data pre-processing and selection of model input/output

Pre-processing the data, such as scaling, is important to ensure that all variables receive equal attention during training. The output variables have to be scaled to be commensurate with the limits of the transfer functions used in the output layer. The input and output variables are scaled between 0.1 and 0.9, as the sigmoid transfer function is used in the output layer. Details of input and output parameters of ANN models are shown in Table 3.

Table 3. Description of input and output parameter in ANN model for section B

Parameter	items	Symbol	Model-1	Model-2	Model-3	Model-4
Excavation method	Excavation step	S_E	Input	Input	Input	Input
Tunnel behavior	Surface settlement (x distance from tunnel center)	S_x	Input	Input	Input	Input
	Subsurface settlement at 8.12m from tunnel center (y distance from surface)	$S_{8.12\text{-}y}$	Input	Input	Input	Input
Design parameter	Young's modulus	E	Output	Input	Input	Input
	Horizontal stress ratio	K_0	X	Output	Input	Input
	Softening parameter	β	X	X	Output	Input
		$\Delta\gamma$	X	X	X	Output

5.4 Studied BPNN architectures and parameters

Despite its versatility, BPNN often faces shape criticism about the high computation for net work training and failure to guarantee its convergence (Suwansawat and Einstein, 2006). Generally, there is no direction and precise method for determining the most appropriate architecture and parameters for the selection of ANN model, although some guide lines are proposed (Hagazy et al., 1994). Trial and error method is the only way to arrive at a suitable learning rate, momentum, number of training cycle and the optimal numbers of hidden node or hidden layer with the criterion error (Neaupane and Adhikari, 2006). The ANN development process is shown in Fig. 10.

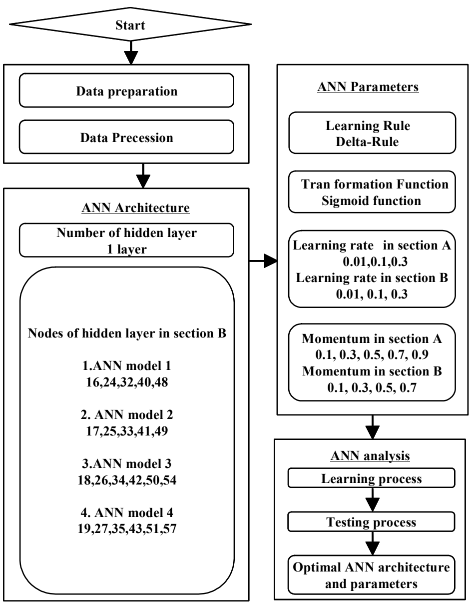


Fig. 10 ANN development process

5.5 Learning process and convergence criterion

Process of optimizing the connection weight and bias is known as training or learning process. The aim is to find a global solution to what is typically a highly non-linear optimization problem. ANN analysis most commonly used for finding optimum weights is BPNN algorithm (Basheer and Hajmeer, 2000). Back-propagation of errors is called an epoch. The iteration step corresponds to an epoch number. In this paper, the convergence criteria are set such that the learning process is terminated when Number of training cycles (Epoch) becomes 400,000 or error of the network becomes less than 0.0001.

5.6 Testing and model validation

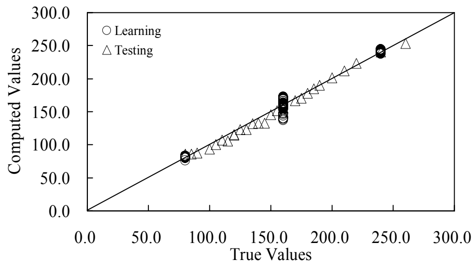
Once the training of a model has been successfully accomplished, performance of the trained model is validated using the testing data, which have not been used as the part of model building process. Testing result is used for the selection of an optimal ANN model. Representative indices that are needed to evaluate the quality of testing resutls are the following 2 indices; the root mean square error and coefficient of determination (R2).

5.7 Results of making ANN model

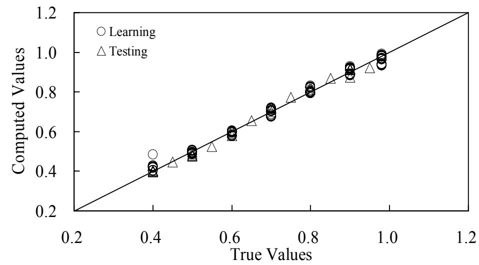
Network development was performed on an IBM-compatible Pentium 4 class machine (598MHz, 248MB RAM). Training took about 6 hours for 600 thousand training cycles. Firstly, parameter identification of E and K_0 was performed initially at the timing of "top heading arrival", assuming an elastic ground behavior. Secondly, β and Δr, two most influential parameters characterizing nonlinear softening behavior, were determined by measured data after "top heading completion". In order to obtain better performance of the ANN model, the ANN architecture was tested with various numbers of nodes per hidden layer, various learning and momentum rates. Despite of learning data being adequately prepared, it is known that quality of an ANN varies depending on chosen network architecture and learning environments. In addition, ANN learning process should be carefully carried out to guarantee generality for further application. After trying many learning and testing procedures, optimal architectures of ANN as well as adopted learning parameters were chosen, that are summarized in Table 4. Fig. 11 show comparison of true values and computed ones using the selected ANN models for sections B. As for the results for section B, a strong correlation between the true and computed values is seen for elastic parameters, E and K_0. In contrast, some scattering is seen especially for reflecting the relative difficulty in estimating a parameter concerned with nonlinear behavior.

Table 4. Learning and testing results of ANN

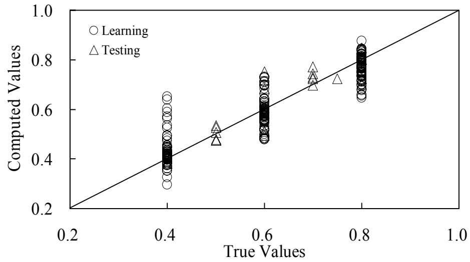
Model	Model-1	Model-2	Model-3	Model-4
	E	K_0	β	$\Delta\gamma$
Learning rule	Delta rule	Delta rule	Delta rule	Delta rule
Transformation function	Sigmoid	Sigmoid	Sigmoid	Sigmoid
Structure	16-16-1	17-25-1	18-18-1	19-27-1
Learning rate	0.1	0.1	0.3	0.01
Momentum rate	0.1	0.5	0.1	0.5
Fianl system error	0.018	0.019	0.534	0.112
Final epoch(cycles)	52	883	40000	40000
Learning RMSE	4.679	0.018	0.069	0.002
Testing RMSE	6.138	0.016	0.062	0.005
Learning R^2	0.999	0.996	0.906	0.986
Testing R^2	0.999	0.996	0.899	0.942



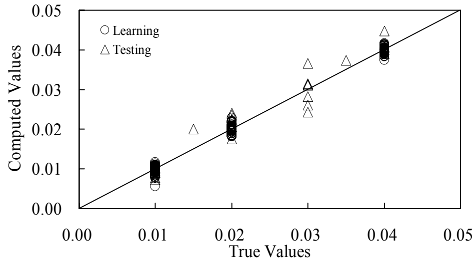
(a) E



(b) K_0



(c) β



(d) Δr

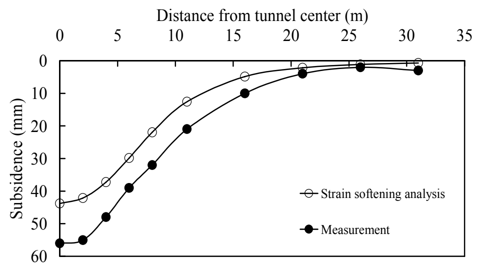
Fig. 11 Comparison of true value and computed one by the selected ANN model in section A

6. Application to the case study

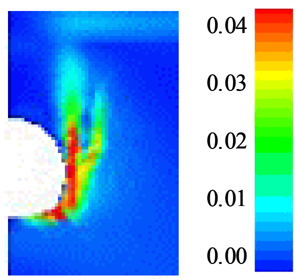
Table 5 show the parameters identified by the optimized ANN models. Strain softening analysis was then performed using identified parameters to simulate all excavation processes.

Table 5. Identified parameter value for section B(*marked value)

Material properties	Section B Layer 1 *Takadate volcanic ash*	Layer 2 *Tengutai volcanic ash*	Layer 3 *Noheji sandy*
$r (kN/m^3)$	14	18	20
E (MPa)	7.9	7.9	127
ν	0.286	0.286	0.286
$\phi(^0)$	30	45	30
c (MPa)	0	0	35
Ration of strength parameter, $\beta_{c,\ \phi(0)} (\%)$	40		
Strain incremental ration, $\Delta\gamma$	0.01		
Ration of anisotropy reduction, $\beta m(\%)$	40		
Horizontal stress ratio, K_0	0.74		



(a) Surface settlement



(b) Maximum shear strain distribution

Fig. 12 Comparison between measured and calculated displacement at invert stage for section B

Fig. 12 shows the comparison of the predicted and measured values in the subsidence settlement and the maximum shear strain distribution for the final stage (completion of invert). In Fig. 12, it shows the development of shear band form tunnel shoulder, which is in good agreement with the results of previous investigation (Lee et al., 2005).

7. Conclusion and discussion

A new form of parameter identification procedure, or back analysis, was proposed for tunneling problems at shallow depth. The finding and results are summarized as follows.

1) Optimally designed ANNs all produced satisfactory results when compared with the measured displacements.

2) Generality of the proposed method suggested that the method can be extended to cope with wide varieties of tunneling problems in which other parameters associated with design, especially support design, could be studied as main unknown parameters.

3) Once this preparation is made, a user only requires measured displacement in field to immediately determine material parameters of ground material and to perform predictive numerical simulation for remaining sequence of construction.

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