

# Application of Artificial Neural Network method for deformation analysis of shallow NATM tunnel due to excavation

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**Abstract:** Currently an increasing number of urban tunnels with small overburden are excavated according to the principle of the New Austrian Tunneling Method (NATM). For rational management of tunnels from planning to construction and maintenance stages, prediction, control and monitoring of displacements of and around the tunnel have to be performed with high accuracy. Computational method tools, such as finite element method, 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 and application of the acquired tunnel information is important for prediction accuracy and improvement of tunnel behavior on construction. Artificial Neural Network (ANN) model is a form of artificial intelligence that attempts to mimic behavior of human brain and nervous system.

The main objective of this paper is to perform the deformation analysis in NATM tunnel by means of numerical simulation and artificial neural network (ANN) with field database. Developed ANN model can achieve a high level of prediction accuracy.

**Key Words :** NATM tunnel, Artificial neural network, Numerical simulation, Field database, Deformation analysis

## 1. Introduction

Successful planning, excavation, lining installation and maintenance of NATM tunnel demands prediction, control and monitoring of tunnel behavior, face stability, surface settlement, gradient and ground displacement with high accuracy.

Of several possible methods of incorporating tunnel construction information for this prediction accuracy and improvement of tunnel behavior, this paper proposes the Artificial Neural Networks

(Rumelhart et al., 1986, 1995). As this method requires firstly preparation of database that contains information to relate input parameters to output parameters, a database is created by performing the acquirement of field data. ANN model are then created studying the database and establishing selected relationships between input and output parameters.

This paper discussed the deformation analysis of NATM tunnel due to excavation stage using ANN analysis with the acquired FEM database and field data.

## 2. Fundamental approach by ANN method

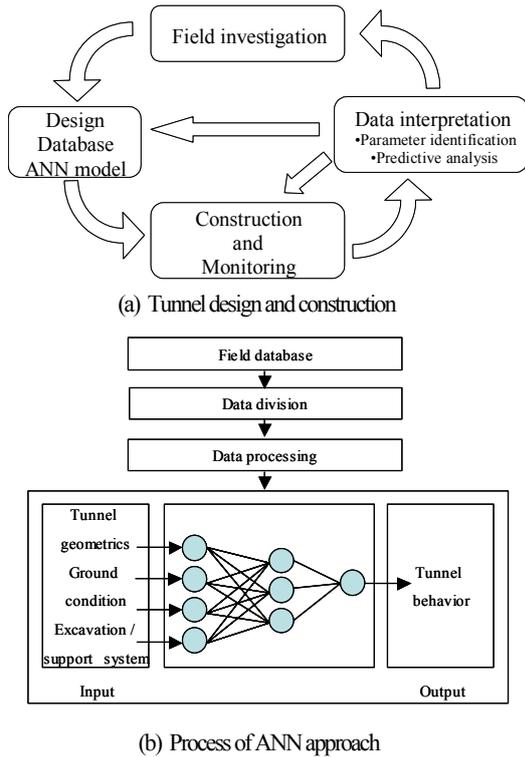


Fig. 1. ANN approach based tunnel design and construction

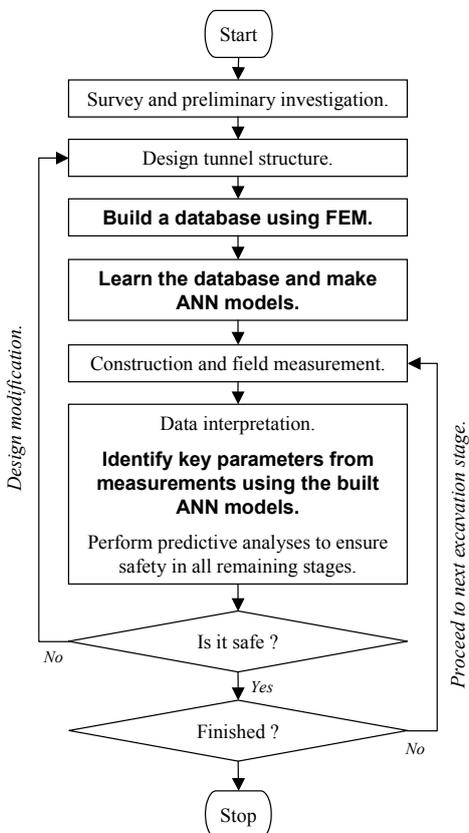


Fig.2 Flowchart of an observational method using ANN technique. Procedures related to ANN are depicted by Gothic font

Numerical analysis or empirical method carried out for the validity the selected support system with preliminary ground estimation on design stage. However, it is difficult to understand that ground estimation over all tunnel section before construction. For reason them, it is carried out the investigation of tunnel information with various measures, as the geology and geo-mechanical properties of the rocks, tunnel face observation recorded, the presence of underground water, surface settlement, subsurface displacement and the tunnel displacement. It is important the using and application of the acquired tunnel information for this prediction accuracy and improvement of tunnel behavior on construction. ANN model is well suited the problem of classification and understanding of the acquired data. Fig. 1 shows a scheme of ANN model for prediction of tunnel behavior. The neural network in the input layer receives tunnel geometric, ground condition, excavation method and support system, as input values. Tunnel behaviors are to be determined from output values.

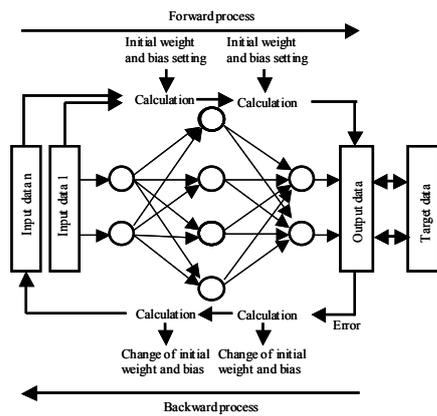
In case of numerical analysis, use of ANN approach can be regarded as one form of back analyses conducted in the framework of a modern observational method, which is depicted in Fig.2. An act of parameter identification as measurement data become available in field should be performed as quickly as possible for safety management reasons in the data interpretation section in the diagram. In order to make this possible, one has to build a database beforehand and let ANN learn about the database in order to establish a trustful ANN model that relates input parameters rationally to output parameters. This learning process, which is the most time consuming, can be performed before construction starts in a design stage, as depicted in Fig.2.

## 3. Outline of artificial neural network model

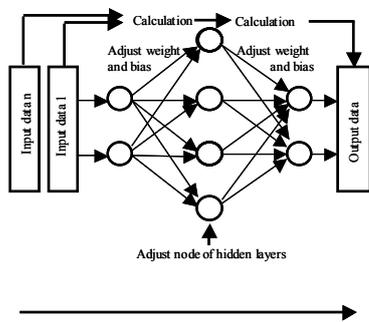
ANN is a form of artificial intelligence that attempts to mimic the behavior of the human brain and nervous system. Back Propagation Neural Network (BPNN) is the most popularly used ANN and it is well suited for problem of classification, prediction, adaptation control, system identification, and so on (Rumelhart et al., 1986; Rumelhart et al., 1995; Basheer, 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. 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. BPNN performs in two phases; learning (training) phase and testing (or validation) phase. During learning of the network, as in Fig. 3 (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. Each path through the entire training pattern is called a cycle or epoch. The process is then repeated as many epochs as needed until the error within the user specified goal is reached successfully. 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. Testing phase is a calculation process that is undertaken after training has been completed, as shown in Fig. 3 (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).



(a) Learning phase



(b) Test phase

Fig. 3. Learning and testing phase in neural network system

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 (Basheer, 2000). Details of the BPNN algorithm are beyond the scope of this study and can be found in Hecht-Nielsen(1987).

Field study is performed by two NATM tunnel of the A and B Project in Japan. That this tunnel excavated through sandy layer under shallow depth and Auxiliary method is applied for face stabilization and water inflow control.

The standard tunnel cross section are given in Fig. 4. Supports reinforcements are rock bolt, shotcrete and steel support as show in Fig. 4. The excavation was conducted by the top heading and three bench cut method. Factors affecting tunnel behavior can be grouped into four major categories as show in Fig. 5.

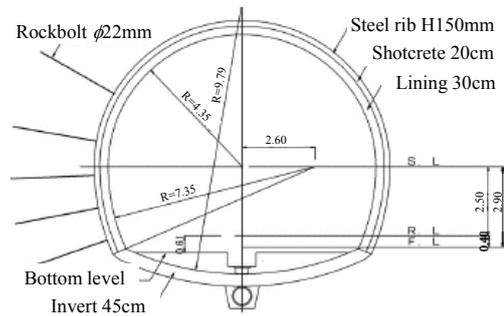


Fig. 4. Details of tunnel cross section

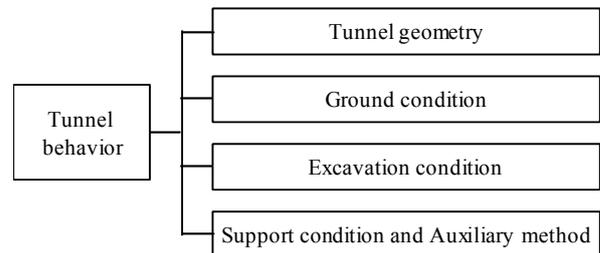


Fig. 5. Four factors affecting tunnel behavior

## 4. ANN analysis with field database

### 4.1 ANN model design and devolpment

The main focus of the ANN approach is to make the prediction model of tunnel behavior through existing data. 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. The neural network in the input layer receives tunnel geometric, ground condition, excavation method and support system, as input values. Tunnel behaviors are to be determined from output values. In this paper, applied ANN analyses are summarized as following three conditions ; 1) ANN analysis I is prediction of tunnel behavior using acquired data before construction, 2) ANN analysis II is prediction of tunnel behavior using data acquired when the tunnel

face arrives at monitored section, and 3) ANN analysis III is prediction of Tunnel behavior using data acquired when the tunnel face is 1D away from the monitored section as shown in Fig.6.

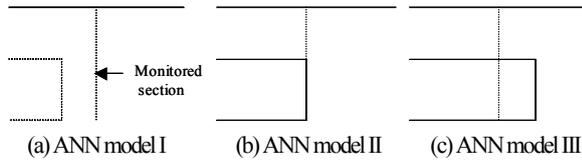


Fig. 6. The proposed ANN models in this paper

Model input parameters are tunnel overburden, ground condition, excavation method, support condition, auxiliary method. And, output parameters of model are tunnel behavior in final excavation.

Table 1. Description of input an output parameter in ANN model I

Category	Parameter	items	ANN model I-1	ANN model I-2	ANN model I-3	ANN model I-4
Tunnel geometrics	Overburden	-	Input	Input	Input	Input
Ground condition	Ground type	clay	Input	Input	Input	Input
		sand	Input	Input	Input	Input
		alt. of strata	Input	Input	Input	Input
Excavation method	Top Heading and Three bench cut method	Shotcrete	-	-	-	Input
		rock bolt(length)	-	-	-	Input
Support condition	rock bolt(number)	H-steel	-	-	-	Input
		Forepiling	-	Input	Input	Input
		Steel pipe forepiling	-	Input	Input	Input
		diameter	×	×	Input	Input
Auxiliary method	Steel pipe forepiling specification	Length	×	×	Input	Input
		number	×	×	Input	Input
		construction degree	×	×	Input	Input
		Face bolt	-	Input	Input	Input
		Face shotcrete	-	Input	Input	Input
		Footing reinforcement bolt	-	Input	Input	Input
Initial tunnel behavior information	Crown	Convergence	-	×	×	×
		Foot settlement	-	×	×	×
		Tunnel behavior in final excavation	Crown	-	Output	Output
Tunnel behavior in final excavation	Convergence	Foot settlement	-	Output	Output	Output
		Convergence	-	Output	Output	Output
		Foot settlement	-	Output	Output	Output

Table 2. Description of input an output parameter in ANN model II and III

Category	Parameter	items	ANN model II-1	ANN model II-2	ANN model II-3	ANN model II-4	ANN model III-1
Tunnel geometrics	Overburden	-	Input	Input	Input	Input	Input
Ground condition	Ground type	clay	Input	Input	Input	Input	Input
		sand	Input	Input	Input	Input	Input
		alt. of strata	Input	Input	Input	Input	Input
Excavation method	Top Heading and Three bench cut method	Shotcrete	-	-	-	-	Input
		rock bolt(length)	-	-	-	-	Input
Support condition	rock bolt(number)	H-steel	-	-	-	-	Input
		Forepiling	-	Input	Input	Input	Input
		Steel pipe forepiling	-	Input	Input	Input	Input
		diameter	×	×	Input	Input	×
Auxiliary method	Steel pipe forepiling specification	Length	×	×	Input	Input	×
		number	×	×	Input	Input	×
		construction degree	×	×	Input	Input	×
		Face bolt	-	Input	Input	Input	Input
		Face shotcrete	-	Input	Input	Input	Input
		Footing reinforcement bolt	-	Input	Input	Input	Input
Initial tunnel behavior information	Crown	Convergence	-	×	×	×	×
		Foot settlement	-	×	×	×	×
		Tunnel behavior in final excavation	Crown	-	Output	Output	Output
Tunnel behavior in final excavation	Convergence	Foot settlement	-	Output	Output	Output	Output
		Convergence	-	Output	Output	Output	Output
		Foot settlement	-	Output	Output	Output	Output

Ground condition in the tunnel used for neural network input are divided into three categories: (1) ground type around tunnel face, (2) the existence of unconsolidated soil and (3) one face record rating of the total geological at the tunnel. Geology type around tunnel face is divided into clay, sandy and alt. of strata. The rating of geology

characteristic at the tunnel face is calculated as according to the Japan standard specifications. The categories of 'excavation method' are divided into two categories: bench cut and three bench cut method. Support conditions are selected in four factors as length and number of rock bolt, shotcrete and Steel beam type. Auxiliary reinforcements were especially considered because NATM tunneling method was commonly used NATM construction in non-stability ground. Five auxiliary reinforcement techniques, forepiling, steel pipe forepiling, face bolt, face shotcrete and footing reinforcement, were major methods as a countermeasure of settlement due to tunneling in Japan. Details of input and output parameters of ANN analysis and various models are shown in Tables 1 and 2.

In ANN analysis I, input parameters are tunnel overburden, initially investigated ground condition, excavation method, support condition and auxiliary method, as design stage. In model I-1, support condition used as the input parameters in the logical variables, which applied to case 1 and did not apply to case 0 in ANN analysis. The input parameters of forepiling and steel pipe forepiling were used as one input variable, which was applied forepiling used as 0 and steel pipe forepiling used as 1. Input variables of steel pipe forepiling specification were not used in ANN analysis. In model I-2, the input parameters of forepiling and steel pipe forepiling were used as two input variable. In model I-3, steel pipe forepiling specifications were used as four variables in ANN analysis. In model I-4, support conditions were used as four input variable. Input parameters of ANN analysis model II included the face rating with ANN analysis model I ones, as tunnel face arrival stage. In ANN analysis model III, input parameters included the initial measure data with the ANN analysis model II.

In this study, field data are obtained by two NATM tunnel in A Project. 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. In data number, 55% of the dataset (102case) was used for training and 45% of the dataset (83cases) was used for testing of the ANN model. After data division, it is important to pre-process the data to a suitable form before they are brought in to an ANN making procedure. 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. Scaling the input variables is not necessary but is always recommended (Hassoum, 1993). 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

(Hegazy 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 development process of ANN model I is shown in Fig. 7.

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 either of the following two conditions ; 1) Number of training cycles (Epoch) becomes 400,000, and 2) Error of the network becomes less than 0.0001. 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.

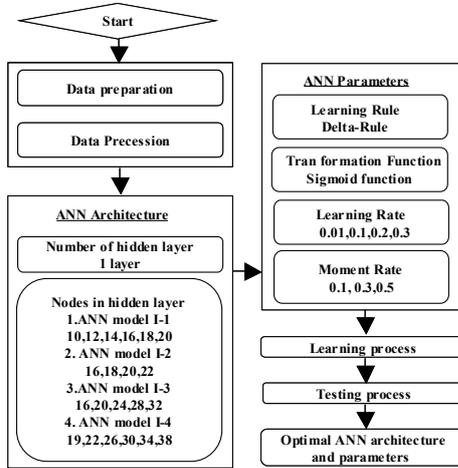


Fig. 7. ANN model I development process

## 4.2 Result of ANN analysis

Prediction of tunnel deformations was performed by ANN analysis with field database for two tunnels. 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. After ANN analysis many trials, the summary of training and testing results are illustrated in Table 3, 4 and 5. The results shown in Table 3, 4 and 5 represented the best performing network that can be achieved in the present study. The proposed analysis of ANN model I-1 is shown in Fig. 8.

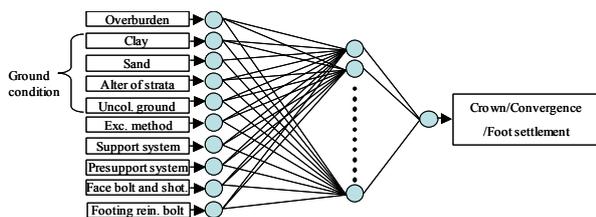


Fig. 8. Studied ANN model I-1

Table 3. Learning and testing result in ANN Analysis I

ANN analysis model I	Final epoch	ANN structure			Learning rate/ Momentum	Learning		Testing		
		Input	Hidden	Output		Correlation	RMSE	Correlation	RMSE	
ANN model I-1	Crown	50000	10	12	1	0.3/0.5	0.92	8.05	0.84	8.49
	Convergence	50000	10	20	1	0.01/0.1	0.80	5.48	0.83	5.05
	Foot settlement	50000	10	12	1	0.3/0.5	0.87	11.95	0.86	9.86
ANN model I-2	Crown	50000	11	18	1	0.2/0.5	0.94	7.14	8.07	0.86
	Convergence	50000	11	16	1	0.01/0.1	0.80	5.48	0.84	4.86
	Foot settlement	50000	11	12	1	0.3/0.5	0.87	11.72	0.84	10.26
ANN model I-3	Crown	50000	16	24	1	0.3/0.5	0.94	7.07	0.86	7.98
	Convergence	50000	16	20	1	0.01/0.1	0.81	5.33	0.83	5.08
	Foot settlement	50000	16	32	1	0.3/0.1	0.88	11.59	0.85	9.99
ANN model I-4	Crown	50000	19	38	1	0.3/0.5	0.94	7.09	0.86	8.02
	Convergence	50000	19	34	1	0.01/0.1	0.80	5.45	0.84	4.91
	Foot settlement	50000	19	19	1	0.3/0.5	0.88	11.59	0.87	9.51

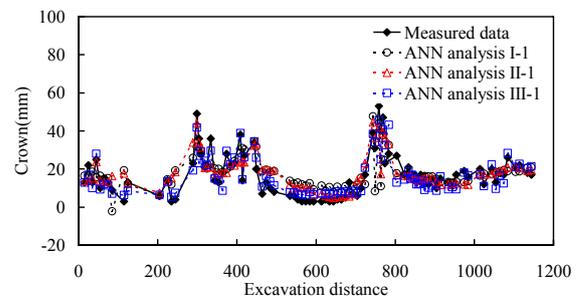
Table 4. Learning and testing result in ANN Analysis II

ANN analysis model II	Final epoch	ANN structure			Learning rate/ Momentum	Learning		Testing		
		Input	Hidden	Output		Correlation	RMSE	Correlation	RMSE	
ANN model II-1	Crown	50000	11	16	1	0.1/0.3	0.94	6.74	0.90	6.90
	Convergence	50000	11	12	1	0.1/0.1	0.87	4.58	0.82	5.21
	Foot settlement	50000	11	14	1	0.1/0.1	0.91	9.76	0.94	6.35
ANN model II-2	Crown	50000	12	20	1	0.1/0.3	0.94	6.95	0.90	6.82
	Convergence	50000	12	16	1	0.01/0.1	0.81	5.41	0.83	5.08
	Foot settlement	50000	12	20	1	0.1/0.5	0.92	9.15	0.93	6.70
ANN model II-3	Crown	50000	17	34	1	0.1/0.1	0.95	6.46	0.90	6.76
	Convergence	50000	17	30	1	0.01/0.1	0.81	5.38	0.82	5.24
	Foot settlement	50000	17	22	1	0.1/0.1	0.92	9.61	0.95	5.59
ANN model II-4	Crown	50000	20	20	1	0.1/0.3	0.94	7.09	0.91	6.66
	Convergence	50000	20	36	1	0.01/0.1	0.80	5.45	0.83	5.10
	Foot settlement	50000	20	28	1	0.1/0.1	0.91	9.75	0.95	5.66

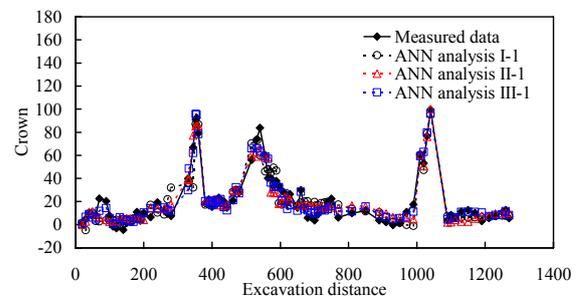
Table 5. Learning and testing result in ANN Analysis III

ANN analysis model III	Final epoch	ANN structure			Learning rate/ Momentum	Learning		Testing		
		Input	Hidden	Output		Correlation	RMSE	Correlation	RMSE	
ANN model III-1	Crown	50000	12	14	1	0.3/0.5	0.99	3.57	0.93	6.57
	Convergence	50000	12	22	1	0.01/0.1	0.92	3.66	0.90	4.00
	Foot settlement	50000	12	18	1	0.1/0.1	0.97	4.88	0.95	4.78

Training and testing results are plotted in Fig. 9 in ANN model I-1, II-1 and III-1. As see in the figure, the neural network model provided good prediction in agreement with measured settlements and its overall performance was much better. ANN analysis III-1 gave the good prediction accuracy compared with ANN analyses I-1 and II-1.



(a) A tunnel



(a) B tunnel

Fig. 9. A measured and predicted results of crown settlement due to excavation length

## 5. ANN analysis with FEM database

### 5.1 Making ANN model

In making an optimized ANN model for parameter identification, measured displacements are input into a model, which outputs linear or nonlinear material properties, as depicted in Fig.10. A trained ANN model has the potential to provide accurate output from input data. Once the ANN determines material properties, an FEM simulation can be performed for prediction of tunneling-induced deformation for following excavation stages.

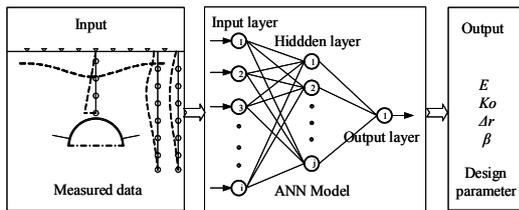
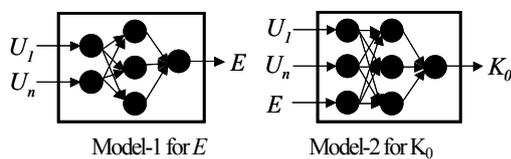


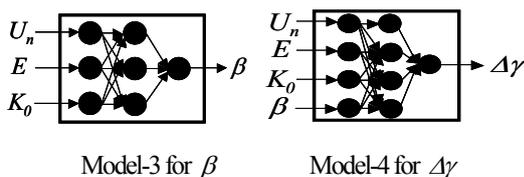
Fig.10 Fundamental flow of actions.

Two different timings,  $T_1$  and  $T_2$ , are chosen for setting up ANN models for respective purposes, as described before. Firstly at  $T_1$ , 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 a model, and  $E, K_0$  are output simultaneously.

However, this set up was found to have some difficulty to obtain those output parameters with high accuracy. Trial and error investigation later revealed that a two-step approach is better. That is that the first ANN, Model-1, is set up such that measured displacement are input to define  $E$  only. The second ANN, Model-2, also uses the same measured displacement and the newly determined  $E$  as input data to define  $K_0$ . These two models, Model-1 and Model-2 are defined at  $T_1$ , the arrival of top heading face, as shown in Fig.11(a).



(a) Two ANN models to be established for  $T_1$ .



(b) Two ANN models to be established for  $T_2$ .

Fig.11 ANN structures of the four models considered

A similar two-step approach is also employed at the second timing,  $T_2$ , which is defined at the completion of the top heading excavation, as shown in Fig.11(b). Model-3 uses measured displacements,  $E$  and  $K_0$  as input, to determine  $\beta$  which indicates ratio of dropped cohesion and friction angle to their original values. The last ANN model, Model-4, uses the measured displacement,  $E, K_0$  and  $\beta$  to define the last key parameter  $\Delta\gamma$  which indicates strain increment during which strength parameters drop from original to residual values. By this strategy, two key parameters controlling elastic behavior of the ground can be determined at the arrival of top heading face. Other two parameters controlling nonlinear behavior can be determined when the top heading excavation is completed. A full set of linear and nonlinear parameters become available then to perform predictive analyses for remaining sequence of tunnel excavation.

Table 6 Materials value used to generate FEM database.

Material properties	Section A			
	Layer 1	Layer 2	Layer 3	Layer 4
	Takadate volcanic ash	Takadate volcanic ash	Noheji sandy	Noheji sandy
$r(kN/m^3)$	14	18	20	20
$E$ (MPa)	5, 10, 15	5, 10, 15	80, 160, 240	100, 200, 300
$\nu$	0.286	0.286	0.286	0.286
$\phi(^{\circ})$	0	0	35	35
$c$ (MPa)	30	45	30	50
Ratio of strength parameter, $\beta_{c, \phi}(\%)$	80, 60, 40% reduction of initial $c$ and $\phi$			
Strain incremental ratio, $\Delta\gamma$	0.01, 0.02 and 0.04			
Ratio of anisotropy reduction, $\beta_m(\%)$	80, 60, 40% reduction of initial $m(=E/G)$			
Horizontal stress ratio, $K_0$	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.98			
Material properties	Section B			
	Layer 1	Layer 2	Layer 3	
	Takadate volcanic ash	Tengutai volcanic ash	Noheji sandy	
$r(kN/m^3)$	14	18	20	
$E$ (MPa)	5, 10, 15	5, 10, 15	80, 160, 240	
$\nu$	0.286	0.286	0.286	
$\phi(^{\circ})$	30	45	30	
$c$ (MPa)	0	0	35	
Ratio of strength parameter, $\beta_{c, \phi}(\%)$	80, 60, 40% reduction of initial $c$ and $\phi$			
Strain incremental ratio, $\Delta\gamma$	0.01, 0.02 and 0.04			
Ratio of anisotropy reduction, $\beta_m(\%)$	80, 60, 40% reduction of initial $m(=E/G)$			
Horizontal stress ratio, $K_0$	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.98			

;Selected value for FEM database

For database generation by parametric FEM analyses, selection of key parameter values was conducted in such a way that the past records from relevant construction or of the lab test results were reflected in the minimum and maximum values of these parameters. Table 6 shows the materials properties used for FEM database. Those parameters for which multiple variations were employed are shown by gray hatch. For example, three different values, namely 80, 60 and 40%, were used for  $\beta$ . Like wise, parameters  $\Delta\gamma, \beta_m$  (ratio of  $m_r$  to its original value  $m_i$ ) and  $K_0$  had 3, 3 and 7 different values. All possible combination of these variables led to 189 patterns ( $3 \times 3 \times 3 \times 7$ ) of

analyses, the results of which are to form the database.

The numbers of analysis cases for Sections A and B in learning and testing processes are shown in Table 7.

Table 7 Number of analysis cases for database generation.

	Section A	Section B
Learning	189	189
Testing	28	35

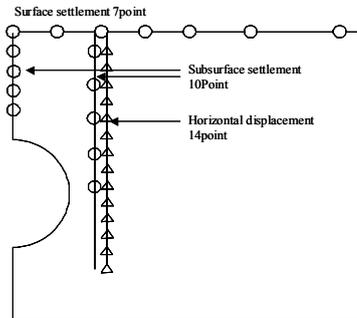


Fig.12 Measurement points for Section A.

Fig.12 shows the measurement point, as input parameter of ANN analysis. For both cross sections,  $E$  and  $K_0$  are determined using measured displacements at the arrival of the top heading; and  $\beta$  and  $\Delta\gamma$  are determined using measured displacements at the completion of the top heading of the tunnel. Details of input and output parameters of ANN models are shown in Table 8.

Table 8 Description of input and output parameter in ANN model for Section A.

Parameter	items	Symbol	Model-1	Model-2	Model-3	Model-4
Excavation method	Excavation step	$S_E$	Input	Input	Input	Input
	Surface settlement (x distance from tunnel center)	$S_x$	Input	Input	Input	Input
Tunnel behavior	Subsurface settlement above tunnel center (y distance from surface)	$S_{0,y}$	Input	Input	Input	Input
	Subsurface settlement at 6m from tunnel center (y distance from surface)	$S_{6,y}$	Input	Input	Input	Input
	Horizontal displacement at 6m from tunnel center (y distance from surface)	$H_{6,y}$	Input	Input	Input	Input
	Young's modulus	$E$	Output	Input	Input	Input
Design parameter	Horizontal stress ratio	$K_0$	X	Output	Input	Input
	Softening parameter	$\beta$	X	X	Output	Input
		$\Delta\gamma$	X	X	X	Output

## 5.2 Results of making ANNs

Firstly, parameter identification of  $E$  and  $K_0$  was performed initially at the timing of “top heading arrival”, assuming an elastic ground behavior. Secondly,  $\beta$  and  $\Delta\gamma$ , 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

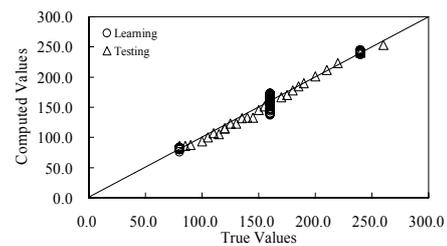
tested with various numbers of nodes per hidden layer, various learning and momentum rates. Despite of learning data being adequately prepared, it is known that quality of an ANN varies depending on chosen network architecture and learning environments. In addition, ANN learning process should be carefully 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 9. The results shown in Table 9 represent the best performing network that was achieved in the present study.

Table 9 Learning and testing results.

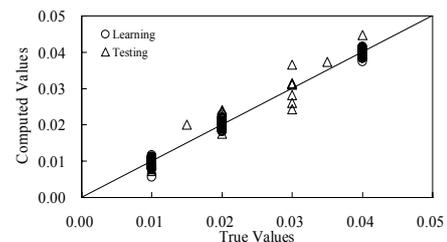
Model	Model-1	Model-2	Model-3	Model-4
	$E$	$K_0$	$\beta$	$\Delta\gamma$
Learning rule	Delta rule	Delta rule	Delta rule	Delta rule
Transformation function	Sigmoid	Sigmoid	Sigmoid	Sigmoid
Structure	32-32-1	33-73-1	34-90-1	35-59-1
Learning rate	0.3	0.01	0.01	0.1
Momentum rate	0.9	0.9	0.1	0.9
Final sys. error	0.019	0.019	0.494	0.019
Final epoch(cycles)	18	2130	40000	40000
Learning RMSE	4.761	0.018	0.066	0.001
Testing RMSE	5.271	0.012	0.054	0.003
Learning $R^2$	0.997	0.996	0.913	0.998
Testing $R^2$	0.996	0.997	0.931	0.973

Model	Model-1	Model-2	Model-3	Model-4
	$E$	$K_0$	$\beta$	$\Delta\gamma$
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
Final 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



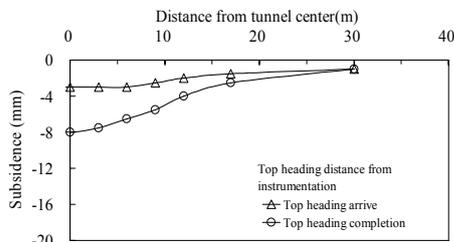
(b)  $\Delta\gamma$

Fig. 13 Comparison of true value and computed one by the selected ANN model in Section A.

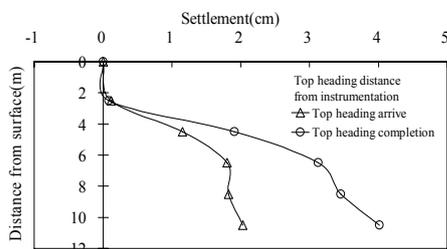
Fig. 13 shows comparison of true values and computed ones using the selected ANN models for Sections A and B. As for the results for Section A, a strong correlation between the true and computed values is seen for elastic parameters,  $E$  and  $A\gamma$ .

In contrast, some scattering is seen especially for  $\beta$  reflecting the relative difficulty in estimating a parameter concerned with nonlinear behavior.

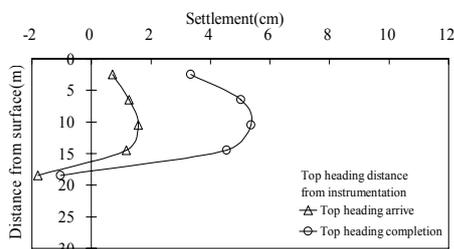
Fig. 14 shows the measured displacement at top heading arrival and completion for Section A.



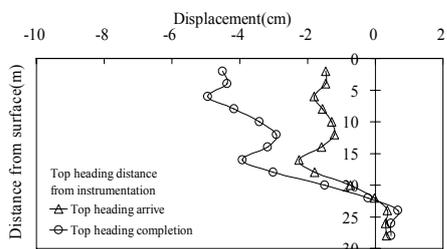
(a) Subsidence



(b) Subsurface settlement above tunnel



(c) Subsurface settlement



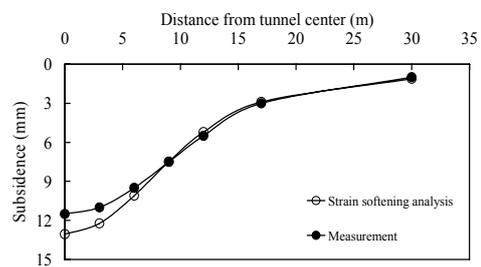
(d) Horizontal displacement

Fig. 14 Measured data in the top heading stage.

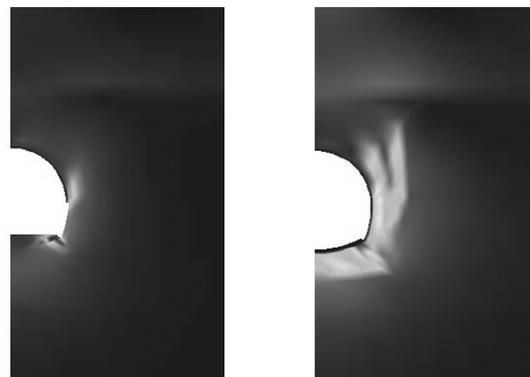
Measured data were used as input data for back analyses based on ANN model. Tables 10 show the parameters identified by the optimized ANN models. Strain softening analysis was then performed using identified parameters to simulate all excavation processes.

Table 10 Identified parameter value for Section A (\*marked value).

Material properties	Section A			
	Layer 1	Layer 2	Layer 3	Layer 4
	Takadate volcanic ash	Takadate volcanic ash	Noheji sandy	Noheji sandy
$r(kN/m^3)$	14	18	20	20
$E$ (MPa)	14.3*	14.3*	229*	286*
$\nu$	0.286	0.286	0.286	0.286
$\phi(^{\circ})$	0	0	35	35
$c$ (MPa)	30	45	30	50
Ration of strength parameter, $\beta_{c, \phi(\%)}$		36*		
Strain incremental ration, $\Delta \gamma$		0.01*		
Ration of anisotropy reduction, $\beta m(\%)$		36*		
Horizontal stress ratio, $K_0$		0.98*		



(a) Surface settlement



(b) Maximum shear strain distribution at T4 (left) and I4 (right). Bright color near the tunnel wall shows strain greater than 1%.

Fig. 15 Comparison of measured and calculated displacement at invert stage for section A.

Figs.15 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).

## 6. Conclusion

The main objective of this thesis is to perform the deformation analysis in NATM tunnel by means of artificial neural network (ANN) and field database. The proposed methodology of using ANN technique in parameter identification problems works with

other engineering methods, such as nonlinear finite element analysis or field measurement conducted onsite. Since the direct source of information from which unknown parameters are determined is measured displacement, the parameters obtained have practical values. Once the network is trained, its running speed is very high, thereby reducing the total time consumed in the analysis. The proposed method based on ANN and field database offers a practical way for prediction final displacement of shallow NATM tunnel, enabling rational safety management scheme to be employed.

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