Jour. of the KGS, Vol. 18, No. 3. June 2002, pp. 113~125

Prediction of Major Parameters of Surface Settlements Due to Tunnelling

터널굴착으로 인한 지반침하의 주요 영향 인자 예측

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요 지

지반의 지표침하를 예측하는 여러가지 경험식들이 있지만, 관련인자들을 동시에 고려하지 못함으로 인하여 불확실한 예측결과를 가져온다. 본 연구에서는 113개의 현장계측자료를 이용한 인공신경망으로 조건에 따른 터널현장의 지표침하를 예측하였다. 지표침하 예측을 위한 현장자료의 입력양식을 제안하였으며, 인자학습을 통해 최적의 인공신경망 모델을 구성하고 RSE의 개념을 통해 터널굴착으로 인한 지표침하에 영향을 미치는 주요인자들을 분석하였다. 본 연구에서 구성한 데이터베이스를 이용하여 인공신경망 엔진을 학습하고 두 가지 현장자료를 통해 검증한 결과, 계측자료의 특성을 효과적으로 반영하는 것을 확인하였다.

Abstract

Although there are several empirical and semi-empirical formulae available for predicting ground surface settlement, most of them do not simultaneously take into consideration all the relevant factors, resulting in inaccurate predictions. In this study, an artificial neural network (ANN) is incorporated with 113 of monitored field results to predict surface settlement for a tunnel site with prescribed conditions. To achieve this, a format for a database of monitored field data is first proposed and then used for sorting out a variety of monitored data sets available in Korea Institute of Construction Technology. An optimal neural network model is suggested through preliminary parametric studies and introduces a concept of RSE (Yang and Zhang, 1997) in sensitivity analysis for various major factors affecting the surface settlement in tunnelling. It is seen in some examples that the RSE rationally enables to recognize the most significant factors of all the contributing factors. Two verification examples are undertaken with the trained ANN using the database created in this study. It is shown from the examples that the ANN has adequately recognized the characteristics of the monitored data sets retaining a generality for further prediction.

Keywords : Artificial neural network, Inflection point, Relative strength of effects, Settlement, Tunnelling

1. Introduction

Tunnel excavation inevitably disturbs the ground and the original stress field, which in turn causes ground movement leading to surface settlement. The ground movements can be large enough to disrupt the function of nearby structures and utilities. Particularly, in urban areas, the freedom of choice of alignment and tunnel

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depth is rather limited. To protect nearby structures from damage, a tunnel designer faces the difficulty in predicting the magnitude and distribution of ground movements to particular ground conditions and construction procedures.

This study is concerned primarily with this problem. Ground movements during tunnel excavation vary in magnitude and distribution depending on several factors related to tunnel geometry, ground conditions and so on. There are several empirical or semi-empirical formulae (Peck, 1969; Deere et al., 1969; Schmidt, 1969; Szechy, 1969; Hansmire and Cording, 1972; Hong, 1984; Bae, 1989) available for predicting ground movement. These empirical or semi-empirical approaches are based on the accumulated experiences over the years. These approaches usually correlate ground movements with one or two variables although the effect of other variables collectively and implicitly in lumped empirical factors has been known. It may be due to inherent restrictions to mathematical expression.

This paper has three main objectives. The first objective is to present a systematic approach for accumulation of extensive field data observed at several tunnel sites. It is in fact obvious that the monitored data from tunnel sites contain a lot of sophisticated physical meanings despite difficulties in description. It is, therefore, necessary to keep accumulating such data, based on a standard format including detailed categories, which will be presented in this study. This prevents confusion and potential data loss.

The second objective is to demonstrate how to utilize the accumulated database to evaluate particular tunnel sites. Thus, an ANN will be incorporated with the database leading to prediction of ground surface settlements based on past tunnel records. A concept of relative strength of effects (RSE) is introduced in sensitivity analysis for various major factors affecting the surface settlement in tunneling (Yang and Zhang, 1997). The third objective is to present a number of verification examples for confirming the approaches proposed in this study.

2. Analytical Methods for Ground Surface Settlements

2.1 Trough of Ground Surface Settlements

Trough of ground surface settlements (TGSS) is a significant aspect in the monitoring of surface settlement (Sagaseta, 1998). A well-known function, the Gaussian normal probability function (GNPF), is chosen for analysing the monitored data to determine the TGSS in a monitoring line and site. In fact, it has been well known that despite irregularity in in-situ monitoring, the TGSS in transverse could be adequately estimated by a Gaussian normal probability function (GNPF) (Schmidt, 1969; Peck, 1969). The GNPF has been also successfully used for evaluating the lateral extension of ground surface settlement from the monitored maximum settlement (Schmidt, 1969; Peck, 1969). Following this approach based on the GNPF, only the analyzed results of raw monitored data will be stored in a database and used in this study because of efficiency in use and generality of the monitored data. Useful equations which describe a TGSS based on the GNPF are mentioned as follows;

When a maximum settlement, $\delta_{s\max}$ and inflection point, i of a TGSS are given, the vertical settlement (displacement), δ_s, along the transverse line to tunnel axis can be calculated by;

$$\delta_s = \delta_{s\max} \exp\left(-\frac{y^2}{2i^2}\right) \tag{1}$$

where it is assumed that $\delta_{s\max}$ takes place at the center of the trough, i is a measure of the trough width (i.e. i is the lateral distance from the tunnel axis to an inflection point of the normal probability function) and y indicates the distance to a certain point along the trough. It is noted here that the volume of the settlement trough along a unit length of tunnel having the same shape as the GNPF is defined as;

$$V_s = 2.5 i \delta_{s\max} \tag{2}$$

Based on the assumption of the fixed volume of the trough, it has been reported that the longitudinal profile of the TGSS would have a cumulative probability form (Attewell and Woodman, 1982). Assuming the ground loss of surface settlement capable of being linearly approximated and all ground deformations taking place retaining constant volume of ground, the vertical displacements at certain positions (x, y) on ground surface are given by;

$$\delta_s = \delta_{s\max} \exp\left[-\frac{y^2}{2i^2}\right]\left\{G\left(\frac{x-x_i}{i_x}\right) - G\left(\frac{x-x_f}{i_x}\right)\right\} \quad (3)$$

$$G(a) = \frac{1}{\sqrt{2\pi}} \int_{-a}^{a} \exp\left(\frac{u^2}{2}\right) du \quad (4)$$

where x is the distance between a point of concern and tunnel face, x_i is the initial position of tunnel face, x_f is the final position of tunnel face and i_x can be replaced by the inflection point, i. Eq. (1) is a simplified form of Eq. (3) in the case of $x \ll x_i$.

To date, these equations have been successfully used for describing a TGSS (Peck, 1969; Attewell and Tayor, 1984 ; Boscardin and Cording, 1989). The $\delta_{s\max}$ and i used in the equations have to be rationally identified because both parameters are sensitive to the settlement results from the equations mentioned above.

2.2 Determination of Maximum Settlements and Inflection Points

In most cases, a maximum ground surface settlement is directly measured and can then be combined with Eq. (3) whilst it is very difficult to determine an inflection point on a trough curve from a limited number of monitored points. The inflection point, however, is a significant parameter governing the settlement zone and depends on several factors such as tunnel geometry and ground conditions. Considering restricted number of conditions, i.e. tunnel geometry and ground conditions, there have been several proposed methods to determine an inflection point. A routine way is to approximate a position, x indicating 0.61 $\delta_{s\max}$ on a δ_s - x diagram where δ_s is monitored vertical settlements and x is horizontal distances from tunnel axis corresponding to the settlements. The resulting i-value using the method is designated as i_e. Another method is to utilize a linear-fitting curve of log δ_s - x^2 diagram. On the fitting curve a point whose settlement is equivalent to 0.61 $\delta_{s\max}$, in turn, can be found. This is called the "best-fit method" (Cording and Hansmire, 1975) by which the i-value determined is designated as i_{bf}. A further method is to use Eq. (2) and to divide the measured volume of settlement trough by 2.5 $\delta_{s\max}$. This is known as the "volume method" and the i-value determined by the volume method is designated as i_v. All three methods are based on the GNPF mentioned in Section 2.1. However, although the measured settlement trough does not perfectly fit the GNPF curve, any of the three methods mentioned can be used to characterize a TGSS from monitored data. If a monitored settlement trough exactly matches with a GNPF curve, the i-values obtained by the three methods should be identical with each other. In addition, Hong and Bae (1995) and Bae (1989) show that the observed i_e-value is very similar to the i_{bf}-value in Seoul and Busan subway tunnels.

Using the methods mentioned above attempts have been devoted to develop charts or analytical equations for estimating i-values and maximum settlements of tunnel sites. Most of the charts and analytical equations, however, are established based on a limited number of factors. Thus, incorporating an artificial neural network, the study proposes a breakthrough for the difficulties embedded in conventional methods. With the proposed methodology, both parameters ($\delta_{s\max}$ and i-value) required in Eq. (3) will be identified considering a variety of "in-situ factors" such as excavation methods, the ground water conditions etc.

3. Relative Strength of Effects (RSE)

A useful concept has been proposed to identify the significance of each 'cause' factor (input) on the 'effect' factors (outputs) using a trained neural network (Yang and Zhang, 1997). This enables us to hierarchically recognize the most sensitive factors affecting ground surface settlements. This is performed incorporating values of 'Relative Strength of Effects (RSE)' (Yang and Zhang, 1997). After a back-propagation neural network has been trained successfully, the neural network is no longer allowed to adapt. The output o_k can be written as;

$$o_k = 1/(1+e^{-e_k}) \tag{5}$$

where,

$$e_k = \sum_j o_j w_{jk} + \theta_k,\ o_j = 1/(1+e^{-e_j}) \tag{6}$$
$$e_j = \sum_i o_i w_{ij} + \theta_j,$$

in which w is a connected weight, θ is a threshold and o_i is the value of input unit. Thus we have

$$o_j = 1/\left(1+e^{-(\sum_j w_{jk}(1/1(1+e^{-(\sum_i wijoi+\theta j)}))+\theta_k)}\right) \tag{7}$$

Obviously, the activation function is a sigmoidal function as shown in Eq. (5), which is differentiable. The variance of o_k with the change of o_i can be calculated by the differentiation of the equation as:

$$\partial o_k / \partial o_i = \sum_{jn} \sum_{jn-1} \cdots \sum_{j1} w_{j_n k} G(e_k) w_{j_{n-1} j_n} G(e_{j_n})$$
$$w_{j_{n-2} j_{n-1}} G(e_{j_{n-1}}) \cdots w_{ij_1} G(e_{j_1}) \tag{8}$$

where $G(e_k) = e^{-e_k}/(1+e^{-e_k})^2$, and o_{j_n}, $o_{j_{n-1}}$, $o_{j_{n-2}}$, $\cdots$, o_{j_1} denotes the hidden units in the *n*, *n-1*, *n-2*, $\cdots$, *1* hidden layers.

Clearly, no matter what the neural network approximates, all items on the right hand side of Eq. (8) always exist. According to Eq. (8), a new parameter RSE_{ki} can be defined as the Relative Strength of Effect for input unit i on output unit *k*.

For a given sample set S={s_1, s_2, s_3, $\cdots$, s_j, $\cdots s_r$}, where, s_j={X, Y}, X={x_1, x_2, x_3, $\cdots$, x_p}, Y={y_1, y_2, y_3, $\cdots$, y_p}, if there is a neural network trained by back-propagation algorithm with this set of samples, the RSE_{ki} exists as;

$$RSE_{ki} = C \sum_{jn} \sum_{jn-1} \cdots \sum_{j1} w_{j_n k} G(e_k) w_{j_{n-1} j_n} G(e_{j_n})$$
$$w_{j_{n-2} j_{n-1}} G(e_{j_{n-1}}) \cdots w_{ij_1} G(e_{j_1}) \tag{9}$$

where C is a normalized constant which controls the maximum absolute value of RSE_{ki} as unit, and the function G denotes the differentiation of the activation function. G, w and e are all the same as in Eq. (8).

It should be noted that the control of RSE is done with respect to the corresponding output unit, which means all RSE values for every input unit on the corresponding output unit are scaled with the same scale coefficient. Hence, it is clear that RSE ranges from -1 to 1.

Compared with Eq. (8), RSE is similar to the derivative except for its scaling value. It is however a different concept from the differentiation of the original mapping function. RSE is a kind of parameter which can be used to measure the relative importance of input factors to output units, and it shows only the relative dominance rather than the differentiation of one-to-one input and output. The larger the absolute value of RSE, the greater the effect of the corresponding input unit on the output unit. Also, the sign of RSE indicates the direction of influence, which means a positive action applies to the output when RSE > 0, and a negative action applies when RSE < 0. Here, a positive action denotes that the output increases with the increment of the corresponding input, and decreases with reduction of the corresponding input. On the contrary, negative action indicates that the output decreases when the corresponding input increases and increases when the corresponding input decreases. The output has no relation with the input if RSE = 0. RSE is a dynamic parameter which changes with the variance of input factors. In the following sections, the RSE will be used for a sensitivity analysis of the influence of factors on the ground surface settlements predicted by a trained neural network.

4. Monitoring of Ground Surface Settlements on Tunneling

4.1 Tunnel Sites and Monitoring Environments

The monitored data have been accumulated from several sectors of Seoul subway (lines 3, 4, 6 and 7) sites, of which specifications are summarized in Table 1. The monitored data for '113' monitoring sections are arranged with respect to the major influence factors on ground settlement. The total extension of the lines 3 and 4 of Seoul subway is approximately 16 km long (7.5 m diameter) and the majority of construction is a twin tunnel varying from 10 to 20 m in depth. Also, in the lines 6 and 7 of Seoul subway, the total extension is about 50 km long with diameter of tunnels ranging between 6.5 and 20 m (13 m on the average). The tunnels comprised either a twin tunnel or a single tunnel varying from 11 m to 54 m in depth. In the twin tunnel, the pillar width between both tunnels varies from 5 to 15 m. A short bench-cut method was adopted for tunnel excavation where the

Table 1. Summary of tunnel geometries and ground conditions for Seoul subway sites

Subway sector	Measured lines	Tunnel depth (m)	Tunnel geometries			Ground water level (m)	Tunnel type*	Constrution Method
			Excavation width (m)	Excavation height (m)	Excavation area (m^2)			
3-A	13	9.8-12.1	6.3-7.5	7.5-7.7	42.1-43.9	2.5-7.5	T	NATM
3-B	5	15.4-16.6	6.2-6.3	7.2-7.7	39.0-42.1	3.5-7.3	T	NATM
4-A	2	10.5-10.6	9.7	8.6	72.7	3.6-3.7	S	NATM
4-B	7	10.2-13.6	6.1-6.3	7.2-7.7	38.1-42.1	3.0-3.5	T	NATM
Bundang line	3	19.6-20.7	10.6-10.0	8.6	79.5-80.0	9.5-10.8	S	NATM
6-A	1	16.8	6.6	6.8	38.8	5.0	S	NATM
6-B	5	14.3-20.6	6.8-11.9	7.3-9.2	43.4-95.5	2.2-5.2	S, T	NATM
6-C	12	15.3-18.0	6.8-8.2	7.8-9.5	46.4-67.9	3.2-5.1	S, T	NATM
6-D	3	16.4-20.1	7.0-23.5	7.1-8.1	47.0-376.0	1.0-4.3	S, T	NATM
6-E	2	16.5-16.9	6.8	7.3	43.4	1.1	T	NATM
6-F	7	11.6-25.1	6.3-21.1	6.9-10.6	38.2-17.4	2.6-4.6	S, T	NATM
7-A	5	18.2-22.6	8.7-11.0	8.0-9.4	61.2-90.4	3.0-7.5	S	NATM
7-B	1	15.0	10.8	8.5	80.3	4.2	S	NATM
7-C	4	17.8-30.7	11.3-15.0	9.7-12.0	96.1-164	2.7-8.4	S	NATM
7-D	40	11.0-54.4	11.0-20.0	9.6-11.6	91.5-184	1.1-5.9	S	NATM
7-E	1	15.0	9.4	8.4	69.3	3.3	S	NATM
7-F	2	13.7-15.4	10.4	7.8	71.0	2.7-2.9	S	NATM
Total 17 sectors	113	Average						
		18.8	**9.8**	**8.9**	**79.2**	**3.8**		

* S : Single tunnel (Double track)
T : Twin tunnel (Single track)

Table 2. General engineering properties of the ground in Seoul subway sites

	Fill	Alluvial Soil	Residual Soil	Weathered Rock	Soft Rock	Hard Rock
Water content (%)	-	28-40	17.0-21.5	9.9-22.7	-	-
Total unit weight (Mg/m^3)	1.6	1.6	1.8-2.0	1.9-2.1	2.5	2.7
Young's modulus (Mpa)	15	15	7.5-65.1	273.7-861.1	0.2-1.1E+4	0.89-6.5E+4
Cohesion, C* (Mpa)	0.01	0.008-0.009	0.0-0.036	1.0-4.0	2.5-5.0	6.0-12.0
Friction angle, ϕ(°)	20	24-34(29)	20-38(31.6)	43-57(49)	36-73(56)	47-66(58)
Poisson's ratio, ν	0.35	0.35	0.33	0.31	0.14-0.23(0.29)	0.18-0.45(0.26)
Permeability coefficient, K_v (cm/sec)	-	-	6.4-9.4E-3(7.9E-3)	-	-	-

* C : undrained shear strength (Cu) for soil and shear strength for rock

length of short bench is about 5 m.

Overburden layers of the tunnels in most cases are composed of weathered granitic rocks, residual soils and alluvial soils. A few tunnel sectors were driven mainly through soft residual soils, however, weathered rocks were sometimes observed in the invert of the tunnels. It was seen that the residual soils in the sites were highly permeable and easily deformed. Due to this, once the upper-half of the tunnel face was excavated, chemical grouts containing "water-glass" were injected from the tunnel face to prevent ground water inflow and improve ground stability (Kim et al., 2001).

As shown in Table 2, overall layout of the ground layers was such that each of the layers was identified with mechanical properties resulting from experiments and in-situ tests. Based on the layout, the monitored data were sorted out and subsequently stored in a database required for training the neural network in this study.

4.2 Analysis of the Monitoring Results

First of all, a general linear least-squares fitting method incorporating a GNPF is implemented into computer codes (Press et al., 1992) which automatically produce a *i*-value and a $\delta_{s\,max}$ value when a monitored settlement profile is given. Using the auto-fitting procedure, all of monitoring settlement data are processed and in turn the calculated results are stored in a database. Within the code, correlation coefficients for each of settlement profiles are also evaluated from which reliability of the monitored data for the adopted GNPF can be estimated. Fig. 1 shows that the average correlation coefficient is approximately 0.84 which means that the monitored data are highly reliable in such a way that the adopted GNPF is considered suitable to be applied to the tunnel sites investigated in this study (Kim et al.,2001).

The overall ranges of *i*-values and $\delta_{s\,max}$ analysed for each of the tunnel sectors are presented in Table 3 with

Table 3. Summary of the parameters relating to surface settlement for Seoul subway sites

Subway sector	δ_{smax} (mm) *	i (m) *	V_s * (m^3)	i/R *	Z_o/D *
3-A	36.0-160.0	10.4-22.4	1.52-6.12	4.1-6.0	0.30-1.70
3-B	22.0-42.0	11.4-25.1	0.63-1.53	3.1-7.1	2.10-2.40
4-A	29.0-30.0	13.5-14.9	0.98-1.12	2.8-3.1	1.08-1.09
4-B	5.0-16.0	10.2-22.4	0.22-0.90	2.9-6.2	1.39-2.15
Bundang line	2.4-3.6	6.4-11.8	0.05-0.07	1.3-2.3	1.94-2.06
6-A	8.0	2.5	0.05	0.7	2.39
6-B	4.2-11.9	4.9-9.9	0.10-0.25	0.9-2.6	1.30-2.80
6-C	5.5-99.5	3.7-11.5	0.07-2.41	0.8-3.0	1.64-2.35
6-D	5.2-12.8	7.6-13.0	0.10-0.40	1.2-2.6	0.90-2.40
6-E	13.1-21.4	5.8-20.3	0.20-1.10	1.6-5.5	2.22-2.27
6-F	4.5-7.3	7.7-11.9	0.12-0.14	1.3-2.9	0.90-2.10
7-A	3.0-5.0	5.9-16.2	0.05-0.31	1.3-5.0	1.70-2.60
7-B	3.0	6.1	0.05	1.2	1.48
7-C	7.0-29.0	4.5-6.3	0.10-0.35	0.8-0.9	1.58-2.78
7-D	3.5-11.0	3.8-11.9	0.06-0.17	0.7-1.6	0.98-4.88
7-E	2.0	8.49	0.04	1.8	1.59
7-F	4.0-8.0	6.0-7.3	0.06-0.15	1.3-1.5	1.43-1.62
Average	21.5	9.8	0.68	2.2	1.93

* δ_{smax} : maximum settlement
I : inflection point
V_s : volume of ground loss
R : tunnel radius (m)
Z_o : tunnel depth (m)
D : tunnel diameter (m)

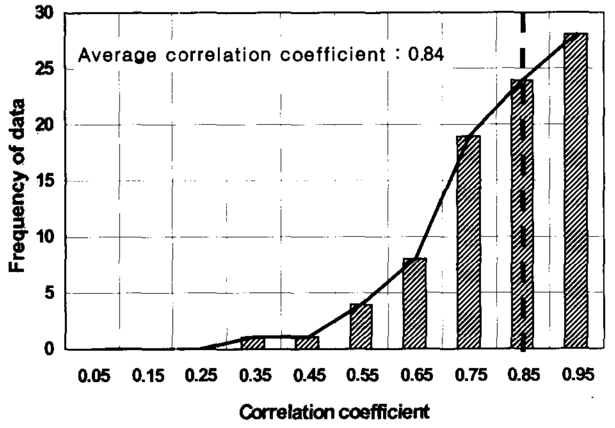

Fig. 1. Correlation coefficients between monitored data and GNPF

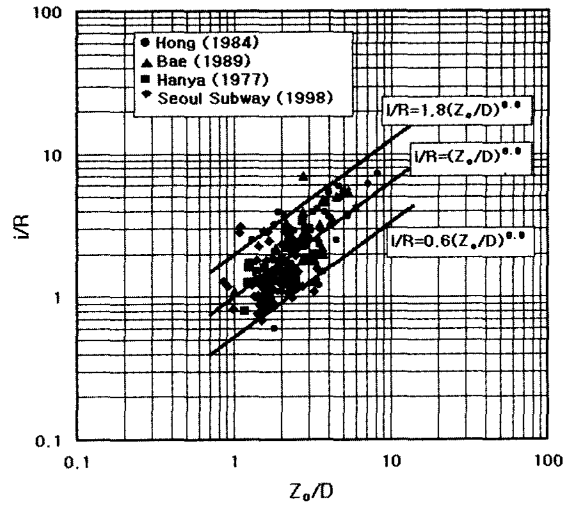

Fig. 2. Relationship between i/R and Z_0/D for field monitored data

a few explanatory factors such as tunnel dimension and depth, etc. It is noted here that all of 113 records collected in this study have been separately stored in a database with a extended number of explanatory factors more than is shown in Table 3. From Table 3, it is clearly seen that the i-values and $\delta_{s\max}$ for the lines 3 and 4 are larger than those for the lines 6 and 7. This is obviously due to differences in inherent conditions such as tunnel depths, tunnel construction methods and ground conditions, etc. However, it is impossible to "quantitatively" explain the reasons why differences between the ground settlements take place although intuitional judgment is available as usual. The quantity of differences and 'the corresponding causes' should also be different from tunnel to tunnel.

Peck (1969) suggested a simple expression for soil, clay and rock incorporating normalized factors (i.e. Z_o/D and i/R) as follows;

$$i/R = K(Z_o/D)^n \tag{10}$$

where K *and* n are constants depending on the ground conditions. In Eq. (10), Attewell and Farmer (1974) suggested values of K = 1.0 and n = 1.0 in the case of stiff clay. Schmidt (1969) also presented K = 1.0 and n = 0.8 in the case of clay. Peck (1969) synthesized the range of K and n-values with respect to certain ground conditions.

In Fig. 2, an attempt was made to plot all of collected data in this study and data available in the literature. Eq. (10) with some parameters is also drawn in Fig. 2. It can be found from Fig. 2 that the range of K-values was from 0.6 to 1.8 and n-value was 0.8 with the K and n-value for the Seoul subway site being estimated as 1.0 and 0.8, respectively (Kim et al., 2001).

4.3 Major Factors Affecting Ground Movements on Tunneling

First of all, in order to categorize field information with monitored data, an adequate database format should be set up. It is also necessary that adopted classification items in the format have to be able to represent characteristics of the data to be classified. The classification items were replaced by major factors affecting ground movements in tunnelling. It is noted here that because of the GNPF being incorporated in this study, ground settlement for each monitoring line is represented by i-value and $\delta_{s\max}$ in the GNPF as shown in Table 4.

Classification items in Table 4 (called as "the major factor" in this study) were derived on the basis of various literature reviews (Kim, 2001) and expertise of experienced engineers. The major factors were first classified into four main categories as shown in Table 4. With conven

Table 4. Major factors affecting ground movement

Category	Parameter	Detailed Items			Input node No.
Tunnel Geometries	(1) Tunnel depth (m)	–			1
	(2) Excavation width (m)	–			2
	(3) Excavation height (m)	–			3
	(4) Tunnel shape*	Circle (0 or 1)			4
		Egg (0 or 1)			5
		Horseshoe (0 or 1)			6
		Special (0 or 1)			7
	(5) Tunnel types*	Single (0)	Twin (1)		8
	(6) Pillar width (m)	–			9
Ground conditions	(7) Host rock mass*	Granite (0)	Schist (1)		10
	(8) Rock mass type and overburden (m)	Weathered			11
		Soft			12
		Moderate			13
		Hard			14
		Very hard			15
	(9) Soil layer type and overburden (m)	Cohesive	Stiff		16
			Soft		17
		Cohesionless	Dense		18
			Medium		19
			Loose		20
	(10) Ground water level (m)	–			21
	(11) Ground water inflow rate (1/min–km)	–			22
Excavation and support conditions	(12) Support methods*	Rock bolt (0 or 1)			23
		Shootcrete (0 or 1)			24
		Steel rib (0 or 1)			25
	(13) Excavation methods*	TBM (0 or 1)			26
		Shield (0 or 1)			27
		Drill and blasting (0 or 1)			28
		Peak (0 or 1)			29
	(14) Excavation types*	Full face cut (0 or 1)			30
		Divided cut	Short bench (0 or 1)		31
			Long bench (0 or 1)		32
			Ring cut (0 or 1)		33
		Temporary invert (0 or 1)			34
		Single side wall drift (0 or 1)			35
		Double side wall drift (0 or 1)			36
	(15) Auxiliary technique*	Forepolling (0 or 1)			37
		Inner grouting (0 or 1)			38
		Surface grouting (0 or 1)			39
		Pipe–roof (0 or 1)			40
		Horizontal jet grouting (0 or 1)			41
	(16) Supporting time*	Early (0 or 1)			42
		Proper (0 or 1)			43
		Delay (0 or 1)			44
	(17) Velocity of excavation (m/day)	–			45
	(18) Excavation length (m/cycle)	–			46
	(19) Drainage system*	Drainage (0)	No drainage (1)		47
Representative parameters for ground movement	Maximum settlement, δ_{smax} (mm)				–
	Inflection point, i (m)				–

* : binary value

tional items such as tunnel dimensions and ground conditions, the major factors also incorporate a number of factors such as tunnel shape, tunnel type etc. Also, the major factors relating to "ground conditions" involve more detailed rock mass and soil layers than in conventional approaches. Host rock mass is divided into granite and schist, whose structures are very different each other, because the two rock types are most common in Korea. Here, it was also intended to consider influences of strata of rock masses and ground conditions on the settlements.

In the category of "excavation and reinforcements", the parameters are selected by main decision factors of tunnel excavation and support condition, and the detailed items such as support methods, excavation methods and types are chosen according to the Korean standard specifications (MOCT, 1997). Support timing and auxiliary reinforcements were especially considered because NATM tunnelling method was commonly used in Seoul subway construction and those four auxiliary reinforcement techniques were major methods as a countermeasure of settlement due to tunnelling in Korea. In addtion, a spread sheet proposed in this study (see Table 4) can be used as a protocol for sorting out further monitored data as well as background information of tunnels.

5. Application of an ANN to Prediction of the Ground Surface Settlements

5.1 Pattern Recognition of ANN

The optimal ANN model is depicted in Fig. 3. In order to confirm if all patterns of training data are adequately recognized by the ANN, training of the ANN was carried out with tolerances of 1.0E-4 and 3.0E-6. Measured *i*-values and $\delta_{s\,max}$ already used in ANN training are then compared with the predicted values by the trained ANN. The average inference error rate is also calculated at each output node. The training data is composed of 113 field results including the major factors (inputs) and representative factors of ground surface settlements (outputs) which have been collected from Seoul subway sites.

The results in Figs. 4 shows that the average inference error rate (AIER) between the inferred values and the measured ones for $\delta_{s\,max}$ are approximately 0.2%.

The recognised aspects from training data are memorised and applied to weight coefficients in the ANN, which I s then capable of being used to predict ground surface settlement when specific tunnel information is given. It should be noted that a prediction using the ANN proposed herein is based on the past monitoring records of tunnels.

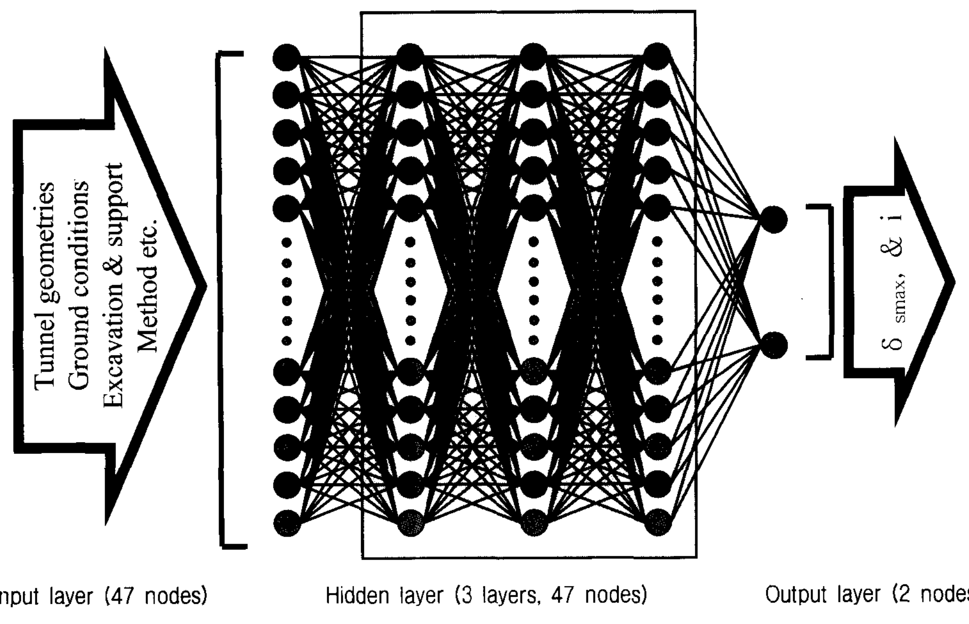

Fig. 3. The optimal architecture of ANN

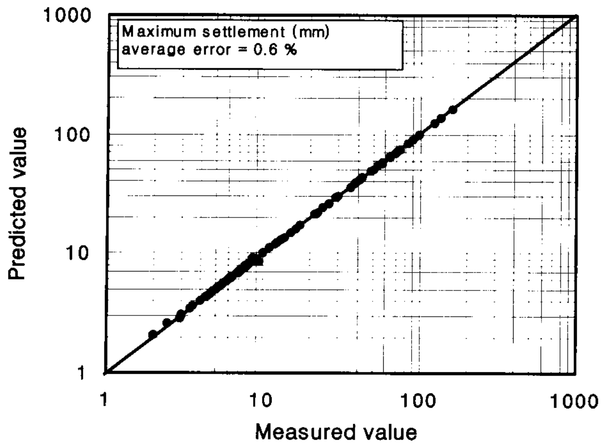

Fig. 4. Comparisons between the predicted and the measured maximum settlement (maximum system error: 3.0E-6)

It means that using capability of pattern recognition and memorisation of the ANN, the prediction of an ANN is automatically improved as more data is accumulated. It is believed that this is an innovative method capable of being "self-enhanced" whenever training data is given, without any restriction.

5.2 Generality of the Trained ANN

To confirm the generality of a trained ANN, simple examples are undertaken with two different sets of 12 data in each, extracted from 113 original data. The first 12 data have got relatively large values of maximum surface settlements, all of them over 36 mm. The second

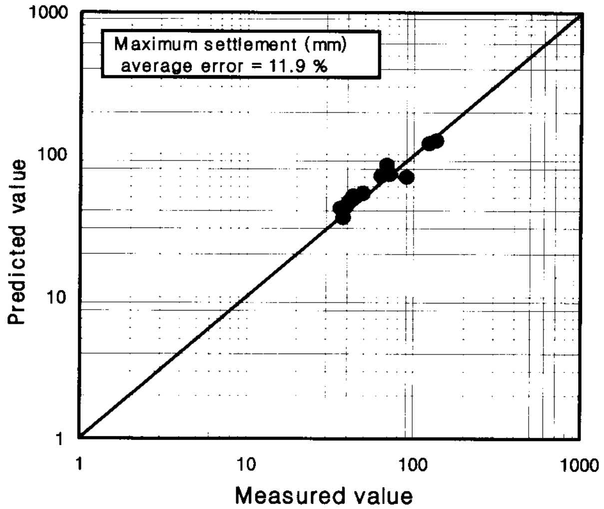

Fig. 5. Inference results for untrained 12 data showing large values of settlement for maximum settlement

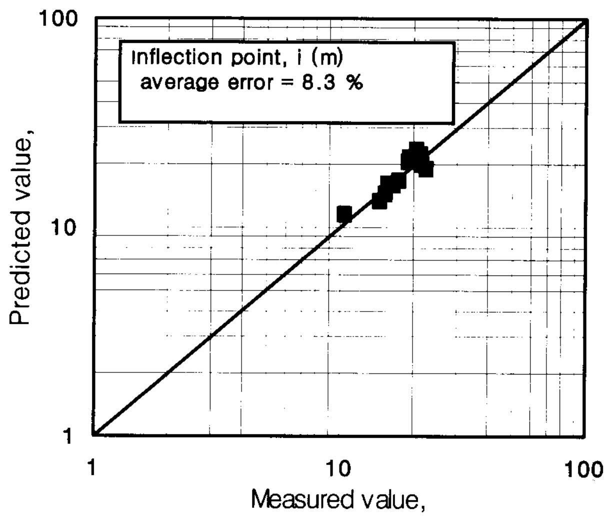

Fig. 6. Testing results of untrained 12 data showing large values of settlement for inflection point

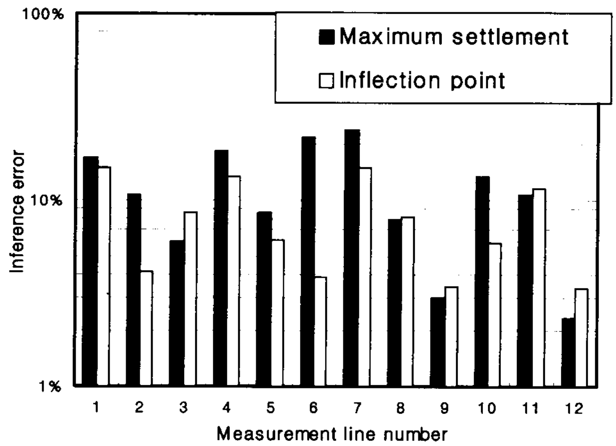

Fig. 7. Inference error results of untrained 12 data showing large values of settlement

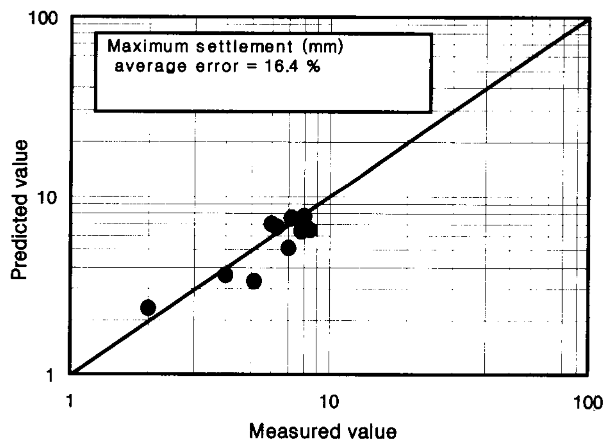

Fig. 8. Testing results of untrained 12 data showing small values of settlement for maximum settlement

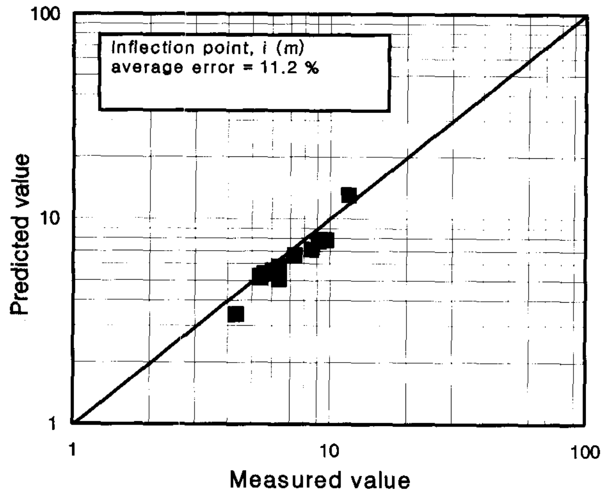

Fig. 9. Testing results of untrained 12 data showing small values of settlement for inflection point

12 data have got relatively small values of maximum surface settlements, all of them less than 9 mm. For both cases, the remaining 101 data are ready to be learnt. It is noted that the 101 data are not the same data in each case. After separate training in both cases, two extracted sets composed of 12 data in each are used for inference (prediction) using the corresponding ANNs to the data sets.

Figs. 5 and 6 show the predicted results using the first data set. The AIERs between the inferred and measured values for *i*-values and $\delta_{s\max}$ for the first data set are approximately 8%and 12% respectively. Fig. 7 also shows the distributions of inference error for each sample. Figs. 8 and 9 show the predicted results using the second data set. The AIERs between the inferred and measured values for *i*-values and $\delta_{s\max}$ in second data set are approximately 11% and 16% respectively.

6. The Quantitative Sensitivity Analysis Based on RSE

Using RSE, examples of sensitivity analysis are undertaken to show how to find significant factors for ground movements with respect to a given tunnel site. Based on RSE values calculated using the ANN, the major factors are hierarchically classified. It is, therefore, obvious that the method can be applied to tunnel sites which have got lots of uncertainties and uniqueness. The sensitive factors given by the method enable engineers to reasonably manage and understand tunnel sites.

Although all of the major factors in Table 4 can be analyzed, 19 representative factors are first selected for simplicity. The sensitivities of these factors to be analyzed are only for maximum settlement in this section. It should be noted that the sensitivities of the major factors for *i*-value are also obtainable.

Fig. 10 shows the average RSE values of the factors calculated for all of 113 field data used in the previous sections. It can be seen in Fig. 10 that "tunnel depth" and "excavation height" are usually the most sensitive in-situ factors at tunnel sites. These factors correspond to "tunnel geometry" and "ground condition" considered

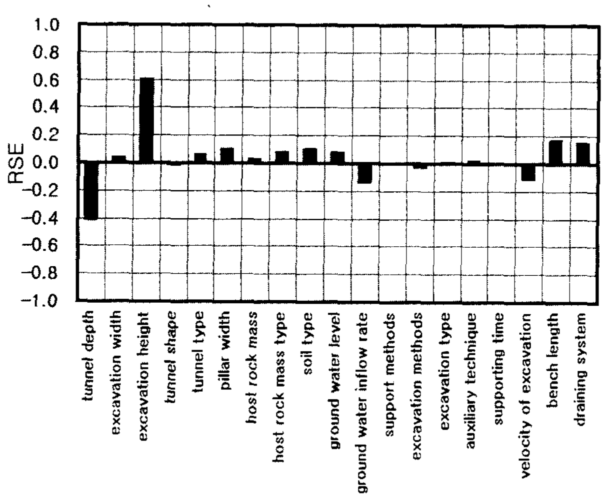

Fig. 10. Average RSE results for the total 113 measured data in Seoul subway sites

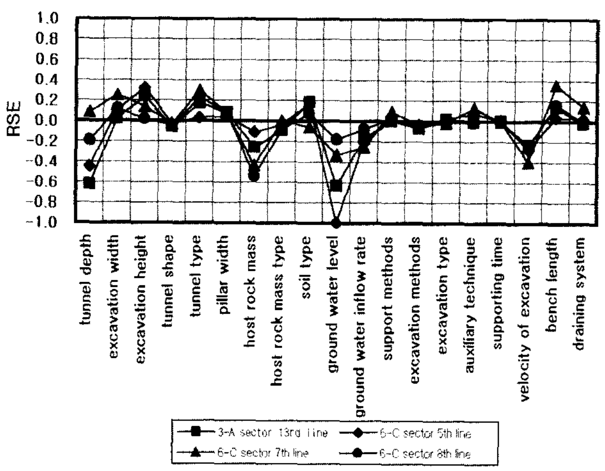

Fig. 11. RSE results for 4 cases of large values of settlement data (above 75 mm in maximum settlement)

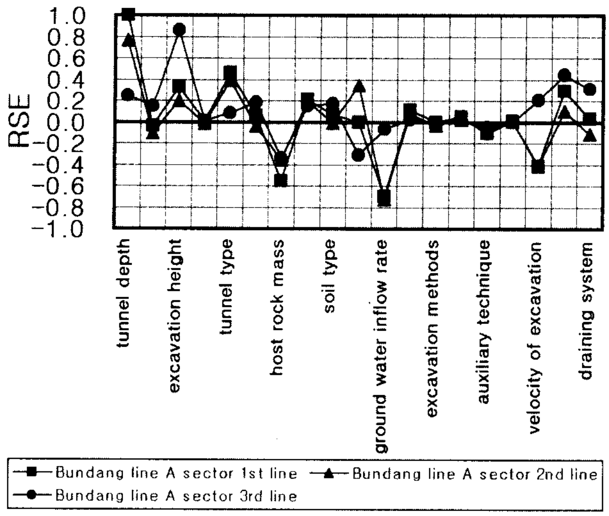

Fig. 12. RSE results for 3 cases of the small values of settlement data (below 3.5 mm in maximum settlement)

in conventional methods. In addition, a positive value of RSE indicates that for example, if "tunnel height" having a positive RSE (see Fig. 10) increases, the larger settlements will take place, and vice versa in the case of negative RSE (i.e. "tunnel depth", etc.).

Fig. 11 shows the individual values of RSE for 4 tunnel sites resulting in relatively large settlements (above 75 mm of maximum settlement). Using these results, it is shown that 5 major factors (i.e. "ground water level", "tunnel depth", "rock mass type", "tunnel excavation height" and "velocity of tunnel excavation") are important factors in ground surface settlement. Fig. 12 shows the individual values of RSE for 3 tunnel sites resulting in relatively small settlements (below 3.5 mm of maximum settlement). The results show that the most significant factors in ground surface settlement (see Fig. 10) are "tunnel depth", "ground water inflow rate", "rock mass type", "tunnel type", and "velocity of tunnel excavation".

7. Conclusions

In this study, a neural-network-based procedure to predict ground surface settlement during tunnelling has been proposed. Incorporating a Gaussian normal distribution function, the settlement profiles collected from various tunnel sites (Seoul subway) are analyzed, leading to two representative parameters (i.e. $\delta_{s\,\max}$ and i-values). These parameters are then stored in a database with background tunnel information for training a neural network. It has been found that the use of both parameters representing monitored raw profile leads to more efficiency in storing as well as in further applications of the database. It has also been seen that a spread sheet proposed in this study (see Table 4) can be used as a "protocol" for arranging further monitored data, as well as background information of tunnels. The protocol is composed of 19 major factors affecting ground surface settlement. It is clear that all of the factors in the protocol have influence on resultant ground movements although the degree of influence can not be recognized with conventional methods. Therefore a useful concept, so-called RSE, has been incorporated in this study with the purpose of determining the most sensitive factors for a given tunnel site. The factors will differ from tunnel to tunnel depending on the conditions.

Monitored ground surface profiles for a total of 113 monitoring lines have been collected to train an optimal neural network chosen and a parametric study has been performed herein. It leads to a rational prediction based on past tunnel records using pattern recognition and the memorization capability of an ANN. The capabilities enable the neural network based prediction to be automatically improved as further information is accumulated, without any restriction. This is an innovative motivation of this study.

Two examples of ground surface settlement prediction have been undertaken. Verification of the methodology has been performed using a pattern recognition test and generality tests. In the pattern recognition test, the average inference errors between the inferred and measured value for $\delta_{s\,\max}$ and i-values are approximately 0.6 % and 0.2 %, respectively. Otherwise, in "generality tests", especially for the case of smaller settlement data, the average inference errors for $\delta_{s\,\max}$ and i-values are about 16 % and 11 % respectively. These results show that the proposed ANN can predict $\delta_{s\,\max}$ and i-values with a high degree of confidence. Furthermore, the most important factors on surface settlement for a given tunnel site are investigated by incorporating a concept of RSE. According to the results of the sensitivity tests using RSE, it can be concluded that there is a hierarchy of these influencing factors for maximum settlement. Overall, the most sensitive factors affecting ground surface settlement during tunnelling are "tunnel depth", "tunnel excavation height", "ground water levels", "inflow rate", "rock mass type" and "velocity of tunnel excavation". It should be noted that the most sensitive factors are changeable variables depending on the conditions of a tunnel site, which can be determined by the RSE analysis.

This research has introduced artificial intelligence for prediction of ground surface settlement based on the accumulated field data. However, it should be noted that the capabilities of such codes in making accurate predictions are entirely dependent on the quality and the quantity of data used in training ANNs. If the data is deficient or training is inadequate, the proposed neural-network-based prediction should be treated with caution. Therefore, the collection and analysis of monitored data should be carefully carried out for guaranteed predictions. A number of investigations are currently being undertaken in the authors' groups to apply the methodology to various critical engineering problems, especially on tunnelling.

Acknowledgements

This research has been performed as a part of the National Research Laboratory project provided by MOST (Ministry of Science & Technology). The authors greatly appreciate their financial support.

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(received on Apr. 30, 2002, accepted on Jun. 8, 2002)