Estimation of the Coefficient of Volume Compressibility of Soils
Using Artificial Neural Network with Batch Learning Algorithm

Noriyuki Kobayashi¹, Takashi Kimata², Masayuki Ishii³, Tatsuro Nishiyama⁴, Yasuhiro Tsukada⁵ and Tomoki Izumi⁶

Abstract: It is important for the geotechnical engineers to predict the amount of the settlements as exactly as possible for the safe design of earth and hydraulic structures. The simple technique called $m_v$ method is often used to calculate the settlement for the small scale structure, and the parameter $m_v$ is properly necessary for the technique. Some researchers have presented empirical formulas for the estimation of $m_v$ that use single or multiple soil parameter models, such as natural water content, unconfined compressive strength, static penetration resistance and others. However, the estimated values of $m_v$ vary widely and there is not necessarily an extremely strong correlation. Moreover, if we try to present a new formula, it is difficult to determine some input soil parameters necessary to overcome complex multicollinearity problems. This study has proposed a simple method that estimate $m_v$ from some soil parameters using the artificial neural network (ANN) with batch learning algorithm developed by Kobayashi et al instead of performing the oedometer test. The optimum combination of input soil parameters has been evaluated and the results of the proposed method have been compared with 4 empirical formulas on the viewpoint of learning efficiency.

Keywords: Artificial neural network; Coefficient of volume compressibility; Extended Bayesian method

1 Introduction

When various hydraulic structures are constructed on ground, stresses increase in the soil strata and the stress increments cause ground settlements (compression and/or consolidation). Especially, if the ground contains saturated clay layer, time depending settlement, that is, consolidation settlement occurs. It is important for the geotechnical engineers to predict the amount of the settlements as exactly as possible for the safe design of earth and hydraulic structures.

Some soil parameters that express the volume change characteristics are used to calculate the settlements and can be obtained by laboratory or field tests. An oedometer test is a kind of laboratory tests performed in geotechnical engineering that measures a soil's consolidation properties (The Japanese Geotechnical Society, 2009). It is a conventional test that simulate the one-dimensional deformation and drainage conditions. As a result of the test, the relation between void ratio and effective stress ($e$-$log\ p$ curve), the compression index $C_c$ that shows the changeability of the void ratio under the applied stress, and the coefficient of volume compressibility $m_v$ that shows the strain increment against the stress increment can be determined.

However, the oedometer test is relatively more time-consuming and expensive than standard index property tests. In the case of small scale construction project, it is difficult to take a long time and cost in order to obtain the compressibility parameters and the simple and economical method for the prediction of settlement is required.

The simple technique called $m_v$ method is often used to calculate the settlement for the small scale structure, and the parameter $m_v$ is properly necessary for the technique. Some researchers have presented empirical formulas for the estimation of $m_v$ that use single or multiple soil parameter models, such as natural water content, unconfined compressive strength, static penetration resistance and others (e.g. Inada, 1960; Takenaka, 1960; Yao et al., 2000; Tamura et al., 2002; Sahoh et al., 2003; Matsubara et al., 2005). However, the values of $m_v$ estimated by these empirical formulas vary widely and there is not necessarily an extremely strong correlation. Moreover, if we try to present a new formula, it is difficult to determine some input soil parameters and necessary to overcome complex multicollinearity problems.

In this study, an attempt has been made to estimate $m_v$ by using an artificial neural network (ANN, Rosenblatt, 1962) in order to conquer the difficulties to derive empirical formulas with a few soil parameters. ANN is a nonlinear and non-paramateric model that is relatively easy to use and understand, while most of statistical methods are parametric model that need advanced knowledge of statistic. This study has proposed a simple method that estimate $m_v$ from some soil parameters using the ANN with batch learning algorithm developed by Kobayashi et al. (2008) instead of performing the oedometer test. And, the optimum combination of input soil parameters has been evaluated and the results of the proposed
method have been compared with 4 empirical formulas from the viewpoint of learning efficiency.

2 Calculation of settlements by \( m_v \) method

2.1 \( m_v \) method

The volume of settlement due to consolidation is often calculated by using \( e - \log p \) method, \( C_v \) method, \( m_v \) method for practical design. In this study, the discussion focuses on \( m_v \) method that is widely applied to predict settlements for small scale structure.

The coefficient of volume compressibility \( m_v \) is the volumetric strain in a clay element per unit increase in stress. The settlement due to a vertical stress increment in soil layer can be determined from the following equation:

\[
S_f = \sum_i m_v \cdot \Delta p \cdot H_i
\]

where \( S_f \): the final consolidation settlement, \( H_i \): the thickness of each consolidated layer, \( \Delta p \): the vertical stress increment.

2.2 Empirical formulas for estimation of \( m_v \)

In this chapter, some empirical formulas for estimation of \( m_v \) instead of the oedometer test have been introduced.

2.2.1 Formula using natural water content \( w_n \)

Tamura et al. (2002) estimated \( m_v \) of each soil layer using \( w_n \) and effective overburden pressure \( P \). This relation between \( m_v \) and \( w_n \) was obtained based on the testing results using terrestrial cohesive soils in Kanto area.

\[
m_v = 1.0 \times 10^{-5} \cdot w_n^4
\]

(2)

\[
A = 1.2 - 0.0015P
\]

(3)

\[
P = P_0 + \Delta P/2
\]

(4)

where \( P_0 \): initial overburden pressure, \( \Delta P \): stress increment.

2.2.2 Formula using natural water content \( c \)

The estimation of \( m_v \) using cohesion \( c \) for Osaka area was presented by Takenaka (1960):

\[
m_v = 1/80c
\]

(5)

Satoh et al. (2003) regressively obtained the relation between \( m_v \) and unconfined compressive strength \( q_u \) in Kanto area.

\[
m_v = 1/52c
\]

(6)

where \( c = q_u/2 \).

2.2.3 Formula using Swedish weight sounding test (SWS)

The relation between shear resistance by SWS (The Japanese Geotechnical Society, 2004) and \( q_u \) was expressed as the following equation (Inada, 1960).

\[
q_u = 45W_{sw} + 0.75N_{sw}
\]

(7)

Yao et al. (2000) proposed the formula that can calculate \( m_v \) using the shear resistance. It was derived from the relation between \( m_v \) and \( c \), \( c = q_u/2 \) and Eq.(5).

\[
m_v = \frac{1}{1800W_{sw} + 30N_{sw}}
\]

(8)

where \( W_{sw} \): the total weight of the loads, \( N_{sw} \): the number of half rotations.

2.2.4 Formula using \( w_n \) and SWS

Matsubara et al. (2005) proposed the equations (9), (10) and (11) considering natural water content \( w_n \), effective overburden pressure \( P \) and shear resistance by SWS. A soil type and \( w_n \) is judged by the specimen sampled with hand auger and the standard \( m_v \) values are set as \( m_{v0} \). Table 1 shows the soil type, \( w_n \) and \( m_{v0} \).

\[
m_v = \alpha \cdot \beta \cdot m_{v0}
\]

(9)

\[
\left\{ \begin{array}{l}
\alpha = \sqrt{0.75/W_{sw}} \quad \text{for } N_{sw} = 0 \\
\alpha = (1 - N_{sw}/40)^3 \quad \text{for } 0 < N_{sw} < 40 \\
\end{array} \right.
\]

(10)

\[
\left\{ \begin{array}{l}
\beta = 1 \quad \text{for } D \leq 2m \\
\beta = \sqrt{2/D} \quad \text{for } D > 2m \\
\end{array} \right.
\]

(11)

where \( D \): depth of soil layer.

The values of \( m_{v0} \) shown in Table 1 are used for the soil of relatively shallow (\( D \leq 2m \)) and median strata (settled by \( W_{sw} = 0.75kN \)). And, the \( m_{v0} \) is corrected by the weighting factor \( \alpha \) and \( \beta \) to derive \( m_v \) for soils of deep and hard strata.

Table 1: Relation between \( m_v \) and \( w_n \)

| soil type                  | \( w_n \) (%) | \( m_{v0} \) (mm/N) |
|---------------------------|---------------|---------------------|
| sand, gravel              | –             | 0.00                |
| diluvial clay             | –             | 0.25                |
| sandy soil                | –             | 0.50                |
| intermediate soil         | \( (35 \leq w_n \leq 50) \) | 0.75                |
| silt                      | \( (50 \leq w_n \leq 70) \) | 1.00                |
| clay                      | \( (70 \leq w_n \leq 90) \) | 1.50                |
| high compressive clay     | \( (90 \leq w_n \leq 120) \) | 2.00                |
| organic soil              | \( (160 \leq w_n) \) | 4.50                |

2.3 Comparison \( m_v^E \) derived from the empirical formulas with those from the oedometer tests

The site investigations including various laboratory tests were performed at 20 construction sites for small scale structures in Fukuyama, Hiroshima Prefecture. The coefficient of volume compressibility \( m_v^E \) derived from the empirical formulas were compared with \( m_v^O \) determined from the oedometer tests. Figure 1 shows the comparison between \( m_v^E \) and \( m_v^O \). Few plots are on the line which means that \( m_v^E \) are equal to \( m_v^O \) and many plots scatter widely. Because all empirical formulas \( m_v^E \) overestimate \( m_v \), the volume of settlement is
calculated greatly. As a result, the design to control a safety side is performed for the structure.
This study has proposed a simple method that estimate \( m_i \) from some soil parameters using the ANN with batch learning algorithm instead of the empirical formulas and oedometer test.

3 Learning algorithm using extended Bayesian method

3.1 Outline of ANN

In this study, the layered feed-forward ANN shown in Figure 2 is applied to the estimation of \( m_i \) (Rumelhart, 1986). This ANN has an excellent capability for the pattern recognition and is adequate to estimate and predict the strongly nonlinear problems difficult to formulate. The instruction signals \( y \) are the correct values in learning of neurons and \( x \) is the input signals of the first layer (input layer). \( \text{net} \) and \( \text{out} \) in Figure 2 are the input signals and output signals, respectively, of the second layers. Because the neurons of the first layer \( L1 \) only transmit information to the next neurons of the second \( L2 \) and do nothing else, the output signals of the first layer is expressed as:

\[
\text{out}^1 = x_j \tag{12}
\]

When the weight coefficient transmitting from the \( k-1 \) th layer to \( k \) th layer is defined as \( w_{j,i}^{k-1,k} \), the input and output signals of the \( j \) th in the \( k \) th layer are expressed as:

\[
\text{net}^k_j = \sum_{i=0}^{L_k} w_{j,i}^{k-1,k} \text{out}^{k-1}_i \tag{13}
\]

\[
\text{out}^k = h(\text{net}^k) \tag{14}
\]

The 0 th neuron \( (i=0) \) stores threshold. \( h(\cdot) \) is the I/O function that describes response characteristic of the neurons and the sigmoid function shown in Figure 3 is applied to it (Eq.(15)).

\[
h(\text{net}^k_j) = \frac{1}{1 + \exp(-\text{net}^k_j)} \tag{15}
\]

The equation that modifies the weight coefficient in back propagation method can be expressed in the following form with the learning ratio \( \eta \).

\[
w_{j,i}^{k-1,k} = w_{j,i}^{k-1,k} - \eta \, \delta^k_j \text{out}^{k-1}_i \tag{16}
\]

\[
\delta^k_j = \left\{ \sum_{i=1}^{L_{k+1}} \delta^k_{j,i} w_{j,i}^{k+1,k} \right\} \text{out}^k_j (1 - \text{out}^k_j) \tag{17}
\]

where \( l \) : iteration number.

3.2 Error function

When \( \text{out}(m) \) and \( y(m) \) describe output and instruction signal of the third layer (output layer) about \( m \) th learning data respectively, the error function can be expressed as:

\[
g(m) = (y(m) - \text{out}(m))^2 \tag{18}
\]

The learning of ANN is equivalent to searching the weight coefficients \( \mathbf{w} \) that minimize the multi-objective function \( \mathbf{G} \). \( \mathbf{G} \) is composed of the functions defined by Eq.(18).

\[
\mathbf{G} = \{g(1), g(2), \ldots, g(m), \ldots, g(N_e)\} \tag{19}
\]

where \( N_e \): number of learning data.
Because the algorithm for learning such as back propagation method sequentially minimizes each component \( g(m) \) using Steepest descent method and finally minimizes the multi-objective function \( G \), the sequential procedure does not necessarily assure minimizing all error functions and it is sometimes difficult to converge and learn efficiently.

In this study, a new learning algorithm is proposed using the extended Bayesian method in order to minimize the error functions for all learning data sets simultaneously.

### 3.3 Learning algorithm using extended Bayesian method

Bayesian method combines prior information with new data to obtain the suitable solutions of nonlinear problems. Because the learning of ANN is regarded as the nonlinear problem, the observation equation applied to ANN is given as follows:

\[
y = f(w) + \epsilon
\]

where \( y \): instruction signal vector \((N_c \times 1)\), \( f(w) \): output signal vector of output layer \((N_c \times 1)\), \( w \): weight coefficient vector \((N_w \times 1)\), \( N_c \): number of weight coefficient, \( \epsilon \): observation noise vector which follows a multivariate normal distribution \( N(0, \sigma_e^2 V_e) \) \((N_c \times 1)\), \( \sigma_e^2 V_e \): covariance matrix of observation noise.

The prior information model is expressed in the following equation.

\[
w = w^* + \delta
\]

where \( w^* \): prior mean vector of \( w \), \( \delta \): system noise vector which follows a multivariate normal distribution \( N(0, \sigma_n^2 V_n) \) \((N_w \times 1)\), \( \sigma_n^2 V_n \): variance - covariance matrix of prior distribution.

The linear approximation of \( f(w) \) is performed by Taylor expansion around \( \hat{w} \) that is the estimation of \( w \) and the sensibility matrix \( X \) is given as follows:

\[
X = \frac{\partial f}{\partial w^i} = \begin{bmatrix}
\frac{\partial f_i}{\partial w_1} & \frac{\partial f_i}{\partial w_2} & \cdots & \frac{\partial f_i}{\partial w_{N_w}} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial f_i}{\partial w_1} & \frac{\partial f_i}{\partial w_2} & \cdots & \frac{\partial f_i}{\partial w_{N_w}} 
\end{bmatrix}
\]

The sensibility matrix \( X \) is regarded as the observation matrix of linear observation equation to estimate \( w \). The evaluation function is expressed in the following equation:

\[
J(w) = (y - Xw)^T V_e^{-1} (y - Xw) + \lambda^2 (w - w^*)^T V_w^{-1} (w - w^*)
\]

where \( \lambda^2 = \sigma_n^2 / \sigma_e^2 \): the parameter that regulates weights of prior distributions and instruction signals (hyper parameter).

When \( w \) that minimize \( J \) is defined as Bayesian estimation \( \hat{w} \), the following equation is established.

\[
\frac{\partial J}{\partial w} = -2X^T V_e^{-1} (y - X\hat{w}) + 2\lambda^2 V_w^{-1} (\hat{w} - w^*) = 0
\]

From the above, the Bayesian estimation \( \hat{w} \) can be given as Eqs. (25) and (26).

\[
\hat{w} = w^* + P(X^T V_e^{-1} (y - X\hat{w})
\]

\[
P = (X^T V_e^{-1}X + \lambda^2 V_w^{-1})^{-1}
\]

Eq.(25) indicates that \( w \) is obtained by adding the adjustment to \( w^* \) which is a provisional solution of the previous step. In this study, the components \( X_{ij} \) of sensibility matrix \( X \) are calculated by the influence coefficient method, given by the following equation.

\[
X_{ij} = \frac{f_i(w + e_j\Delta w_j) - f_i(w)}{\Delta w_j}
\]

where \( \Delta w_j \): \( j \) th infinitesimal increment of \( w \), \( e_j \): unit vector of which \( j \) th component is equal to 1, \( f_i \): \( i \) th component of \( f \). The first term of numerator in Eq. (27) is obtained by calculating forward with adding the weight coefficient \( w \) to infinitesimal increment \( \Delta w_j \).

### 4 ANN learning

Twenty (20) data sets that are the results of some experiments and investigations in Fukuyama, Hiroshima prefecture are selected as the learning data to construct ANN model. The coefficient of volume compressibility \( m \), obtained by the oedometer test is subjected to logarithmic conversion and were normalized, and then treated as the instruction signal \( y \). \( m \) is assumed to be affected by natural water content \( w_n \), wet density \( \rho_t \), thickness of consolidation layer \( d \), clay content \( CC \), unconfined compressive strength \( qu \) and/or weight of the load of the swedish weight sounding test \( W_{sw} \). Some of the data are treated as input signals. In order to find an appropriate combination of input signals, ANN models composed of various combinations of input signals are trained.

#### 4.1 Results of multiple regression analysis

At first, the input signals that affects \( m \) are examined using multiple regression analysis. In these analyses, three cases are undertaken, namely, Case A in which 6 parameters (all input signals) are adopted as the descriptive variables and

| input signal | standard partial regression coefficient |
|--------------|----------------------------------------|
| \( w_n \)    | 0.56 0.37 0.31                        |
| \( \rho_t \)  | 0.98 0.78 0.56                        |
| \( d \)       | -0.22 -0.22 -0.36                     |
| \( W_{sw} \)  | -0.21 -0.23 -            |
| \( qu \)      | -0.14 - -0.17                     |
| \( CC \)      | -0.05 -0.12 0.01                    |

| multiple correlation coefficient | 0.60 0.59 0.58 |

Table 2: Results of multiple regression analysis
Case B, C in which 5 parameters including either one of $q_u$ and $W_{sw}$ are adopted as the descriptive variables because both of them denote the shear resistance of soil.

Table 2 shows the results of the multiple regression analysis. The values of standardised partial regression coefficient $b'$ related to $\omega_n$ and $\rho_t$ become large and the two parameters affect $m$ strongly. In contrast, the value of $b'$ related to $CC$ is small and $CC$ has little influence on $m$. Between $m$ and the soil strength can be regarded as a negative correlation. Because $W_{sw}$ reflects the influence of confining pressure in the ground, the weight of $W_{sw}$ on $m$ is larger than that of $q_u$. Figure 4 shows the comparison between $m_{v}^M$ derived from the multiple regression analysis and $m_{v}^T$, $m_{v}^M$ become closer to $m_{v}^T$ than $m_{v}^E$ determined from the empirical formulas. However, the variances from $m_{v}^T$ are still large.

In all cases, the multiple correlation coefficients is small. Therefore, it is found that there is a limit to the evaluation of $m$ using the linear analysis such as multiple regression analysis.

4.2 Results of ANN learning

The ANN case models composed of various combinations of input signals are shown in Table 3. The circles in Table 3 denote the parameters selected as an input signals.

|       | $\omega_n$ | $\rho_t$ | $d$ | $q_u$ | $W_{sw}$ | $CC$ |
|-------|-------------|-----------|-----|-------|----------|------|
| Case1 |     ⃝      |     ⃝    |     ⃝ |     ⃝ |    ⃝    | ⃝   |
| Case2 |     ⃝    |     ⃝    |     ⃝ |     ⃝ |    ⃝    | ⃝   |
| Case3 |     ⃝    |     ⃝    |     ⃝ |     ⃝ |    ⃝    | ⃝   |
| Case4 |     ⃝    |     ⃝    |     ⃝ |     ⃝ |    ⃝    |    ⃝ |
| Case5 |     ⃝    |     ⃝    |     ⃝ |     ⃝ |    ⃝    |    ⃝ |
| Case6 |     ⃝    |     ⃝    |     ⃝ |     ⃝ |    ⃝    |    ⃝ |

Figure 5 shows the relation between $m_{v}^S$ derived from learning stage of ANN and $m_{v}^T$ in Case 1, 2, 3 and 4. The input signals $\omega_n$, $\rho_t$ and $d$ in Case 1 have no information about shear resistance of soil. However, some plots in Figure 5 are on the line which means that $m_{v}^S$ are equal to $m_{v}^T$ and the identification accuracy is relatively higher. In contrast, many plots scatter widely in Case 2 and 3 in which only $q_u$ or $W_{sw}$ denoting shear resistance is adopted as the input signal.

The relation between $m_{v}^S$ and $m_{v}^T$ in Case 4, 5 and 6 is shown in Figure 6. In Case 4, $q_u$ and $W_{sw}$ is added to Case 1, respectively. The precision of $m_{v}^S$ are improved in both Case 1 and 5 has a higher accuracy than $m_{v}^S$ in Case 4. It is found that $W_{sw}$ is a more effective factor of consolidation than $q_u$. In Case 6, $CC$ is added to Case 5. The precision of $m_{v}^C$ in Case 6 is even lower than $m_{v}^C$ in Case 1 and 5, and many plots in Figure 6 are under the line which means that $m_{v}^C$ are equal to $m_{v}^T$. Therefore, the consolidation settlement using $m_{v}^C$ in Case 6 tends to be underestimated.
The differences between $m_v^c$ and $m_v^f$ are quantitatively evaluated by the modeling efficiency (Loague et al., 1991) expressed by Eq. (28). When $EF$ is closer to 1, the difference between $m_v^c$ and $m_v^f$ is smaller. The values of $EF$ in 6 cases are 0.639, 0.578, 0.559, 0.857, 0.890, 0.620, respectively, and the identification accuracy in Case 5 is highest. Therefore, it is found that the optimum combination of input signals for the estimation of $m_v$ is $w_{sw}$, $\rho_v$, $d$ and $W_{sw}$.

$$EF = \frac{\left\{ \sum_{i=1}^{n} (h_0 - h_i)^2 \right\} - \left\{ \sum_{i=1}^{n} (h_0 - h_i)^2 \right\}}{\left\{ \sum_{i=1}^{n} (h_0 - h_i)^2 \right\}}$$

(28)

5 Conclusions
In order to overcome the difficulties in inducing the empirical formulas with a few soil parameters, this study has proposed a simple method that estimate the coefficient of volume compressibility $m_v$ from some soil parameters using the ANN with batch learning algorithm instead of performing the oedometer test. $m_v$ has been assumed to be affected by natural water content $w_{sw}$, wet density $\rho_v$, thickness of consolidation layer $d$, clay content $CC$, unconfined compressive strength $q_u$ and/or weight of the load of the Swedish weight sounding test $W_{sw}$, and all or some of them are treated as input signals. In order to find an optimum combination of input signals, ANN models composed of various combinations of input signals were trained. The conclusions drawn from this study are the following:

1. Because $m_v$ are overestimated by the empirical formulas, the volume of settlement is calculated with significant error. As a result, the design to control a safety side is performed for the structure.
2. Because the multiple correlation coefficients is small, it is found that there is a limit to the evaluation of $m_v$ using the linear analysis such as multiple regression analysis.
3. The ANN with batch learning algorithm can be applied to predict $m_v$ of soil.
4. The optimum combination of input signals for the estimation of $m_v$ is $w_{sw}$, $\rho_v$, $d$ and $W_{sw}$.

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