The 2016 World Congress on
Advances in Civil, Environmental, and Materials Research (ACEM16)
Jeju Island, Korea, August 28-September 1, 2016

ANN Based Estimation of SWCC Fitting Parameters for Korean Weathered Soil Considering In-Situ Characteristics

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ABSTRACT

Soil water characteristic curves are important for assessing the instability of unsaturated soil slopes. There are three main approaches to estimate the SWCC based on a grain size distribution and other soil factors; i.e., correlating water contents at each matric suction with soil factors, estimating fitting parameters of an analytical equation, and physico-empirical models. In this study, the second approach using an approximate Fredlund and Xing equation consisting of four fitting parameters is considered. The SWCC (fitting parameters) being a function of pore size distribution and stress state vary across different sites, and thus necessitating the need for setting up a site-specific database for reasonable landslide hazard predictions under an extreme rainfall condition. Therefore, an SWCC fitting parameter estimation model has been developed via an artificial neural network (ANN) using soil samples collected from eight regions in Korea. The developed model considers four factors namely: percentage of sand, percentage of clay, water content, and void ratio. The final ANN model, resulting in respective training, testing, and validation RMSEs of 0.99, 0.80 and 0.70, consisted of two hidden layers; 8 neurons in first layer and 4 neurons in second layer. The final ANN model can be used to predict the volumetric water content at any specific matric suction (including residual and saturated) as an input for large or small scale landslide hazard evaluation in any of the eight regions in Korea.

1. INTRODUCTION

The increase in frequency and intensity of extreme rainfall events in Korean peninsula has resulted in the increase of catastrophic landslides. Most of the natural slopes before rainfall exist in an unsaturated condition which governs the infiltration under wetting depth progression and hence, the stability condition. The soil water characteristic curve expressing the relationship between the volumetric water content and the matric suction is influential in controlling the transient seepage at shallow soil depths (Chiu et al., 2012). The direct estimation using laboratory tests being time-consuming and expensive has led to the indirect estimation of the soil water characteristic curve using the grain-size distribution curve (Arya and Paris, 1981;

Fredlund et al., 1997). The indirect estimation can be classified into three main approaches (Zapata, 1999): correlating water contents at each matric suction with soil factors, estimating fitting parameters of an analytical equation, and physico-empirical models. An ANN based model, to predict the fitting parameters for Korean weathered granite soils, developed by Lee (2003) did not consider factors related to in-situ moisture content and void ratio, and hence it was suitable to be considered in the analysis of man-made structures. Thus, in this study we developed another model incorporating the in-situ characteristics existing in the natural slope through 53 data. The Fredlund and Xing (1994) model was selected for fitting the experimental data in this study owing to the following reasons: flexibility of the model in fitting variety of datasets; meaningful parameters with the effect of each distinguishable from the other; faster convergence for the best fit parameter estimation than Van Genuchten (Lee, 2003; Sillers, 1997).

2. METHODOLOGY

In this study, a multi-target ANN model was used to consider the non-linear relationship existing among the independent and the dependent factors. The ANN modelling mainly consists of a combination of several layers including the diverse neurons, and the output value of a certain neuron is multiplied by a weight before inputting the value to the other neurons. A net is formed by adding all values, which are the multiplication of each weight and output value from the previous neurons, and then the output value to be used as input data to the next neuron can be calculated through the activation function as shown in the equations below:

$$net = \sum_{i=1}^{n} W_i X_i \tag{1}$$

$$output = f(net - b) \tag{2}$$

where X_i is the input value to a certain neuron, W_i is the weight for the corresponding input value, b is the bias of each neuron, and f is the activation functions like step, sigmoid, tangent functions, etc. A multi-perceptron, consisting of an input layer, two hidden layer, and an output layer, is used for the ANN modelling since the usage of a single-layer perceptron is limited to linearly separable data sets. An error back-propagation learning algorithm is usually used in a multi-layer perceptron to determine the neural networks architecture. The difference between the output target value and the actual value is reduced through modulations of the weights and bias. The training of the ANN model is stopped using the Levenberg-Marquardt technique when either the maximum epoch is reached or the mean-square-error (mse) converges below a mean-squared-error threshold (0.005). The mean-square-error is calculated as:

$$mse = \frac{1}{n} \sum_{k=1}^{n} \left[O(k) - T(k) \right]^2 \tag{3}$$

where, O(k) is the predicted soil water characteristic parameters, T(k) is the experimentally fitted soil characteristic parameters, and n is the total number of the data.

3. DATABASE AND MODEL DEVELOPMENT

For developing the model, soil were sampled from about 53 sites in eight regions; Inje, Dongrae, Yongi, Yesan, Yeongi, Danyang, Chuncheon and Busan. Table 1 shows the descriptive statistics of basic soil properties in the sites.

Table 1: Descriptive statistics for weathered soil samples

	Minimum	Maximum	Average	Standard deviation	Variance
% sand	32.49	99	78.12	14.49	210.06
% fines	0.28	43.57	5.336	7.07	50.09
Water content	0.55	37.64	16.73	5.36	28.70
Void ratio	0.54	1.27	0.837	0.155	0.024

The sampled soils were tested in the lab using the Tempe pressure cell. The experiments were conducted by placing saturated soil samples on top of the saturated high air entry disk inside the cylinder of the Tempe pressure cell. The air pressure, set at a desired matric suction, is then applied until the soil sample reaches an equilibrium; i.e., the matric suction in the soil sample becomes equal to that applied. Time to an equilibrium depends on the thickness of the soil sample, and permeabilities of specimen and high entry disk. The water content in the sample at end of the test corresponding to the matric suction at equilibrium was measured by oven-drying (Fredlund and Rahardjo, 1993). The measured soil water characteristic data were fitted using the three parameter Fredlund and Xing model (1994). The model uses three parameters; a, n, and m to provide a continuous soil water characteristic curve over the entire soil suction range. In this model, a, n and m are related to air entry value, pore size distribution of soil, and asymmetry, respectively. The a parameter having units of suction, corresponds to an inflection point on the curve and is related to the soil air entry value. The equation is given as follows:

$$s = \frac{1}{\left[\ln\left[e + \left(\frac{\psi}{a}\right)^n\right]\right]^m} \tag{4}$$

$$\theta = \frac{s}{\left[\ln\left[e + \left(\frac{\psi}{a}\right)^n\right]\right]^m} \tag{5}$$

The parameters of the model are related to basic soil information such as, void ratio, in-situ water content, % sand, and % fines.

The ANN model was ran using Matlab neural network toolbox, distributing 70%, 15%, and 15% of the total 53 data for the training, testing and validation dataset, respectively. The basic soil parameters of void ratio, % sand, % fines and water content were used in the input layer while a, n, m and degree of saturation were obtained as the results (Fig.1). The training was conducted for the 37 data using the Levenberg-Marquardt (Marquardt, 1963) back propagation algorithm for different number of neurons in the two hidden layers. After several trial and error using different number of neurons, the best model was obtained for four independent factors with 8 and 4 neurons, respectively. Fig.2a shows that a R-square of 0.99 was obtained indicating a highly well-trained model. The training of the model was stopped at the optimum number of iteration when the validation dataset reached a high R-square of 0.83 (Fig.2b). The generalization and predictive performance of the trained model was checked for the 8 dataset which was not used for training of the model. The result in Fig.2c showing a R-square of 0.89 points to a reliable model with high predictive performance. From these results the significant influence of the selected basic soil properties on the soil water characteristic curve parameters can be observed.

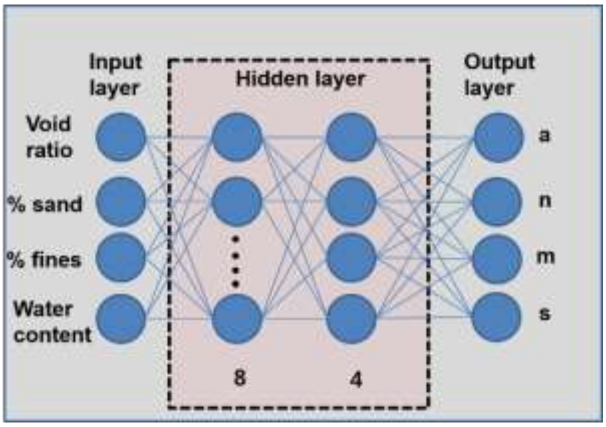

Fig.1: ANN network (4-8-4-4) for SWCC parameter estimation

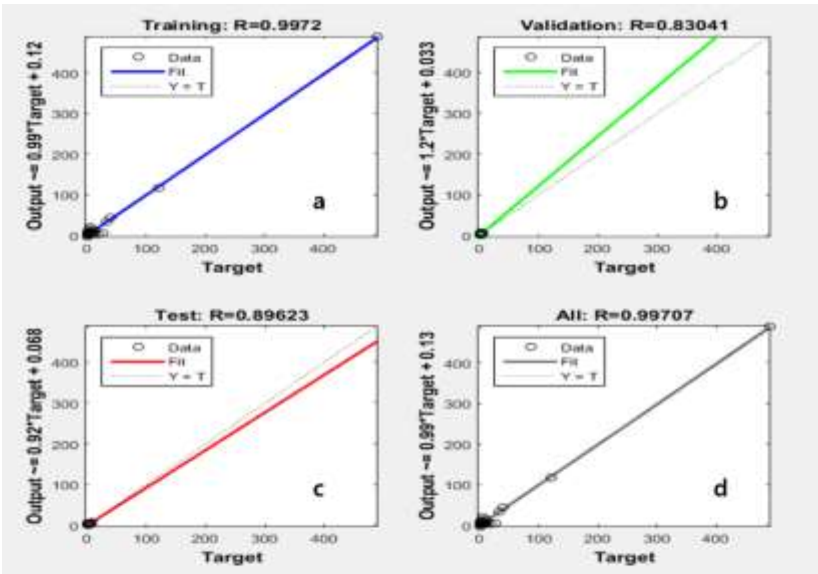

Fig.2. ANN model performance (4-8-4-4): (a) Training; (b) Validation; (c) Testing;(d) Average.

5. CONCLUSION

In this study an ANN based method was suggested for reliable estimation of soil water curve for weathered soils in Korea. This was achieved through the experimental measurement of the soil water characteristics curve for the 53 data with the basic soil information such as void ratio, water content, % sand, and % fines. The ANN network of 4-8-4-4 configuration using tangent-sigmoid transfer function was adopted since a reliable performance indicated by a high R-square of 0.89 was obtained. The result also shows a significant influence of the selected basic soil information parameters on the prediction of the soil characteristic water curve.

ACKNOWLEDGEMENT

The present work was supported by the Public Welfare & Safety Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT & Future Planning (NRF-2012M3A2A1050974) and Korea Ministry of Land, Infrastructure and Transport (MOLIT) through the U-City Master and Doctor Course Grant Program.

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