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A thermal conductivity estimation model applicable to Korean weathered granite soils

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ABSTRACT

Thermal conductivity of soil ground has a great influence on the performance of Ground Heat Exchangers (GHEs). In general, it significantly depends on soil's density (or porosity) and water content since they are decisive factors which control the interface area for heat transfer between soil particles. This study conducted a lot of thermal conductivity experiments with varying soil's porosity and water content, and developed a database of thermal properties for weathered granite soils. Based on the database, 3D Curved Surface Model and Neural Network Model were suggested for estimating the thermal conductivity. The developed model was validated by comparing model's predictions with measured values of new thermal conductivity data, which had not previously been used in developing the model. As for the 3D Curved Surface Model, the normalized average values of training data and test data were 1.079 and 1.078, respectively with the variation of 0.158 and 0.130, and the predictions became unreliable in a low range of thermal conductivity considering the dispersion. As for the Neural Network Model, „Logsig-Tansig' transfer function combination with 9 neurons gave the highest accuracy for the estimation. The normalized average values of training data and test data were 1.006 and 0.954, respectively with the variation of 0.026 and 0.098. It can be concluded that Neural Network Model gives much more reasonable results than 3D Curved Surface Model.

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1. INTRODUCTION

In general, ground-surface temperatures fluctuate with seasonal air temperature, while the temperature at deeper levels (below a depth of 15m from the surface) remain stable at about 16℃ because the overlying ground acts as an insulator (Olgun et al 2012). Ground-Source Heat Pump (GSHP) system utilizes these relatively constant temperatures as an energy source by circulating the fluid inside the heat exchangers. Owing to its tremendous and costless stored energy, the system can guarantee a high heat efficiency compared to other heating/cooling systems. In order to exploit this ground energy, the heat exchanger is installed in the GSHP system and buried in various ways. Traditionally, vertical closed-loop heat exchanger are commonly used among others and it requires high drilling costs at the initial stage of construction. Recently, however, to resolve a high construction cost, the heat exchangers are installed inside existing piles of the building, which is called energy pile. It plays a role as not only a structural supporter but a carrier for heat exchange. Because the heat exchangers are just installed inside existing piles without any drilling, the borehole length is limited to about 20m. Therefore, energy pile's heat exchange is usually performed in a shallow depth, and hence the design of energy pile should be conducted considering the ground thermal properties in a shallow depth.

In the design of shallow depth energy pile, the most important factors are the thermal conductivity of ground in which the heat exchangers are installed. Therefore the reasonable estimation of ground's thermal properties facilitate the efficient design of GSHP system by providing more accurate estimates of thermal energy transfer between the ground loop heat exchanger and the surrounding soil (Hart and Whiddon 1984). Nevertheless, there are not enough databases of thermal properties which reflect the characteristics of Korean weathered granite soils especially in the shallow-depth ground. Moreover, it is uncertain that the current estimation models are applicable to Korean weathered granite soils. In this reason, this study focused on a Korean weathered granite soil, and developed a database of thermal properties. Based on the database, 3D Curved Surface Model and Neural Network Model were suggested for accurate estimation of thermal conductivity. Finally, the developed model was validated by comparing model's predictions with measured values of new thermal conductivity data, which had not previously been used in developing the model.

2. THERMAL CONDUCTIVITY TEST

In general, there are two kinds of methods for obtaining the thermal conductivity: non-steady state method and steady state method. Steady state method measures heat velocity which keeps the temperature constant between two different materials. The representative equipment of steady state method is Heat Flow Meter (Fig. 1). Though the procedure of test is simple, however, it takes long time and if the surface of materials is unstable, it may give the result with low accuracy. Meanwhile, the non-steady state method is based on a linear heat source theory. The material properties are determined while the sample temperature is still changing. In this reason, the main advantage of non-steady state technique is short measurement time. TP08 Probe (Hukseflux) is a primary equipment using the non-steady state method. It only takes

200s to obtain the results.

This study measured soil's thermal conductivity by using TP08 probe and it is composed of some parts as shown in Fig. 2: ① wire ② base, ③ needle, ④ temperature sensor ⑤ heating wire ⑥ thermocouple junction. As shown in Fig. 2, once heat is injected by needle probe, it causes a thermo electromotive force, and then thermal conductivity can be measured in a non-steady state.

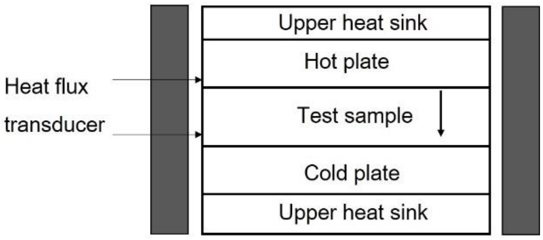


Fig. 1 Schematic design of HFM equipment

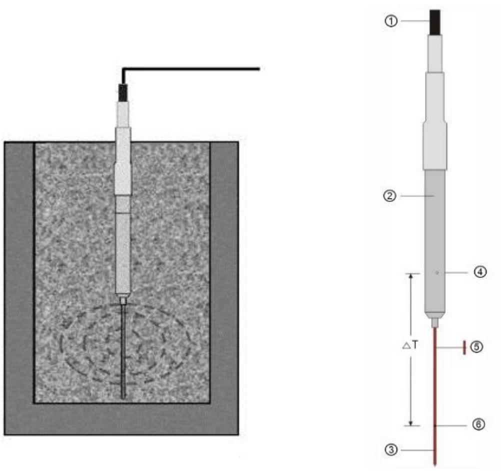


Fig. 2 Schematic layout of TP08 Probe (Hukseflux)

3. TEST MATERIALS

The weathered granite soils from Sejong Yongi (W1), Gangwon Pyungchang (W2), Junnam Damyang (W3), Busan Geumjung (W4) and Joomoonjin sand (S1) in Korea were sampled and used for thermal conductivity tests. Table 1 shows the basic properties of these samples. The porosity of undisturbed sample is about 0.4~0.5. S1 (Joomoonjin sand) is poorly graded soil, while W1~W4 (weathered granite soils) are well graded soils. Also as shown in Fig. 3, the weathered granite soils can be regarded as non-plastic soils due to its low fine proportion.

The mineral quantitative analysis (XRD) for the weathered granite soils was performed (Table 2, Fig. 4). Thermal conductivity of soil particle (λs) was obtained by

Geometric mean based model. As for the Joomoonjin sand (S1), the ratio of quartz appeared as more than 90%. It means that there are great differences in the mineral composition ratio between weathered granite soils and joomoonjin sand. It implies that it may be difficult to apply current models to weathered granite soils in Korea.

Table 1 The basic properties of samples

Soil	porosity*	C_u	C_c	G_s	USCS*
S1	0.45	2.06	1.05	2.65	SP
W1	0.44	13.80	1.67	2.58	SW
W2	0.46	7.80	1.01	2.55	SW
W3	0.52	7.67	1.23	2.56	SW
W4	0.53	12.83	1.47	2.54	SW

*porosity (undisturbed)
*Unified Soil Classification System

Table 2 Results of Mineral Quantitative Analysis (XRD)

Soil	Mineral portion (%)								λ_s
	Quartz	Microcline	Albeit	Kaolin	Orthoclase	Muscovite	Illite	Chlorite	(W/mK)
S1	92.0								7.0
W1	28.2	21.8	24.6	13.8	-	5.9	4.2	0.8	3.504
W2	28.6	19.0	28.5	9.0	-	6.8	-	1.1	3.491
W3	40.7			30.8	17.4		11.1		6.044
W4	38.5	-	23.5	17.9	19.2	-	-	0.6	3.875

*Provided by KIGAM

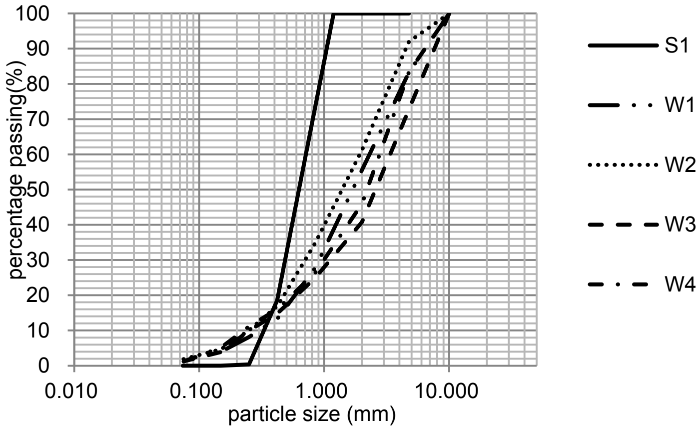


Fig. 3 Particle size distribution of samples

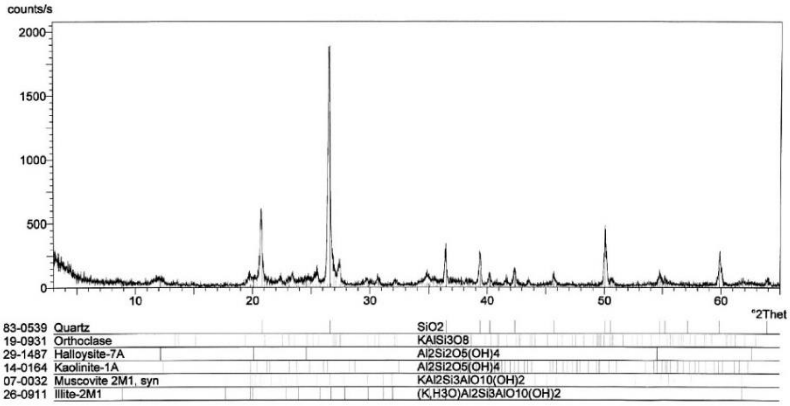


Fig. 4 Results of Mineral Quantitative Analysis (W3)

4. DEVELOPMENT OF ESTIMATION MODEL

This study suggested a thermal conductivity estimation model considering porosity and water content based on the experimental database. Based on the established database, a 3-D Curved Surface Model (Fig. 5) was developed, and its equation can be represented as a function of porosity and water content. The ranges are limited to use: 0~25% for water content and 0.25~0.65 for porosity, respectively.

$$f(\omega, n) = 0.66 + 20.57 \cdot \omega - 0.94 \cdot n - 3.51 \cdot \omega^2 - 28.6 \cdot \omega \cdot n \quad (1)$$

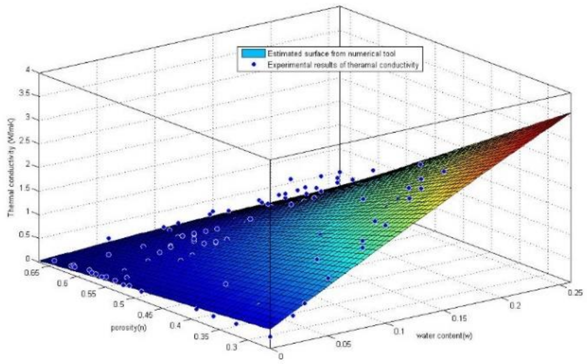


Fig. 5 3-D Curved Surface Model based on experimental data

5. THERMAL CONDUCTIVITY NEURAL NETWORK MODEL (TNNM)

The Neural Network Model is a mathematical model which imitates the network system in human's brain. This model is widely used in diverse geotechnical engineering areas such as estimation of consolidation settlement and undrained shear strength of soils. This study developed Neural Network Model based on the thermal conductivity data for estimating the thermal properties of Korean weathered granite soils.

Neural Network Model consists of multilayer neural network which includes input layer(I) – hidden layer(H) – output layer(O). In each layer, there are several neurons replicating a standard unit of human's nervous tissue and they are connected with neurons in other layers by specific weight. Input data of each neuron in layers are multiplied by weight and the sum of these values are handled by transfer function. The building process of Neural Network Model can be divided into two steps. The first step is a training phase, in which the weight between neurons in each layers are adjusted. In this step, Neural Network Model is able to learn about the optimum weight that can generalize the given data by itself. Next step is a testing phase where the constructed model is verified by comparing the prediction data with experimental data.

5.1 Database of weathered granite soils

This study developed thermal conductivity database of weathered granite soils sampled in Sejong, Pyungchang, Geumjung and Damyang area. About 100 data points were used in constructing and verifying Neural Network Model. Of all data, 74 points data were used as „training data' in order to develop a Neural Network Model and 30 points of randomly selected data were used as „testing data'. Each input data was normalized to data of which range exists within [0, 1] to conduct Neural Network Model training efficiently.

Table 3 Characteristics of weathered granite soils used in training and testing job in NNET

Region	Porosity(n)	Water Content (%)	Thermal Conductivity of Soil particle (W/mK)	#200 Sieve Pass Efficiency (ratio of fine-grained soil)	Cu	Cg
Sejong	0.48~0.61	0~20.0%	3.50	1.60	7.68	1.23
Pyungchang	0.49~0.58	0~22.3%	3.49	1.80	7.80	1.01
Geumjung	0.55~0.64	0~24.4%	3.88	1.20	12.83	1.47
Damyang	0.57~0.67	0~25.8%	6.04	1.20	13.80	1.67

5.2 Optimization technique

Error back-propagation algorithm employed in training of multilayer neural network was used for this study because input and output data show non-linear relationship. Also Levenberge-Marquardt technique provided in Matlab Toolbox was used in the optimization technique for weight and bias. Training phase was stopped when it reached a max. Epoch or mse converges (Eq. 2) below mean squared error goal (0.005).

$$mse = \frac{1}{n}\sum_{k=1}^{n}(a(k)-t(k))^2 \tag{2}$$

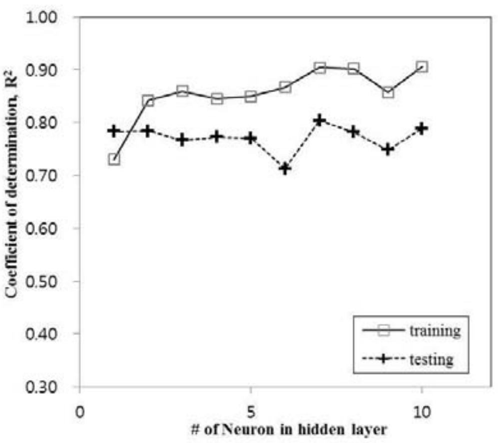
where $a(k)$ is predicted thermal conductivity data by Neural Network Model, $t(k)$ is experimental measurement data of thermal conductivity and n is the number of total data.

5.3 Decision of optimization model

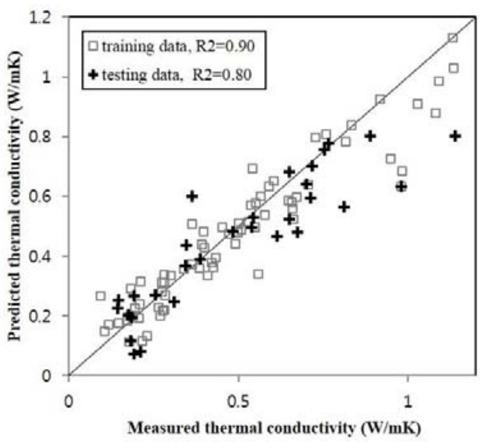
In order to build a Neural Network Model, five fundamental input parameters of water content, porosity, thermal conductivity, coefficient of uniformity and coefficient of curvature were selected. Since the accuracy of Neural Network Model depends on the number of neurons in hidden layer and type of transfer function, different types of transfer function(Log-sigmoid, Tan-sigmoid, Linear) were applied and the number of neurons varied from 1 to 10(Table 4). Analysis was performed to find predictive accuracy (R2) of model considering training data and testing data and the model showing the highest accuracy was finally selected as the optimized Neural Network Model- thermal conductivity estimation model.

Table 4. TNNM transfer functions and comparison of R2 by the optimum number of neurons

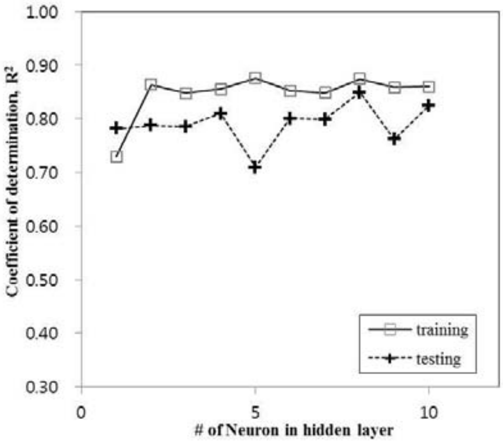
Transfer function	The number of neurons	training data R^2	testing data R^2
Logsig-Linear	7	0.90	0.80
Logsig-Logsig	8	0.87	0.85
Logsig-Tansig	9	0.93	0.84
Tansig-Tansig	6	0.85	0.82



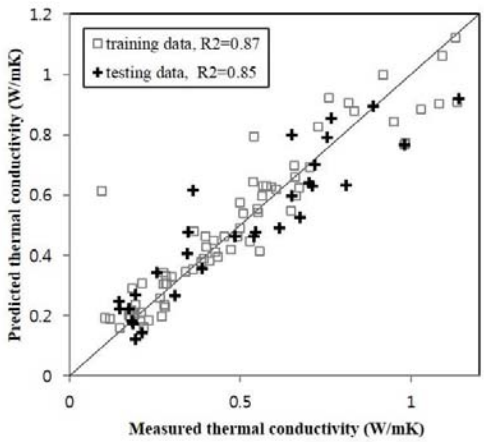
(a) R^2 by number of neuron in hidden layer



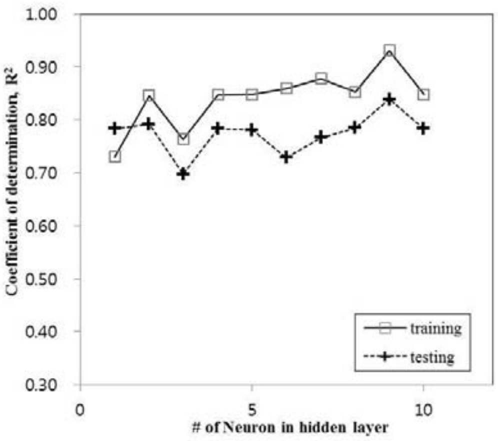
(b) Logsig(7)-Linear model



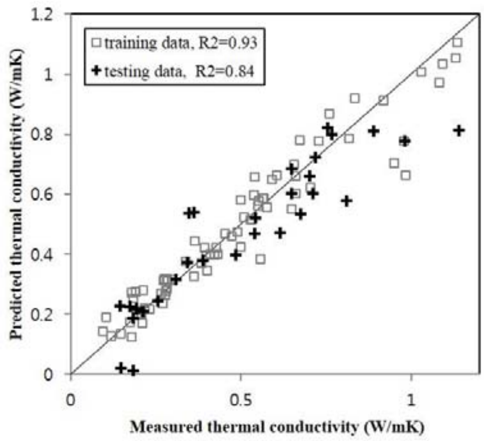
(c) R^2 by number of neuron in hidden layer



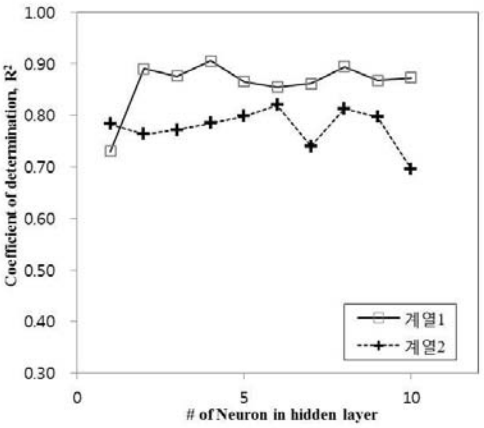
(d) Logsig(8)- Logsig model

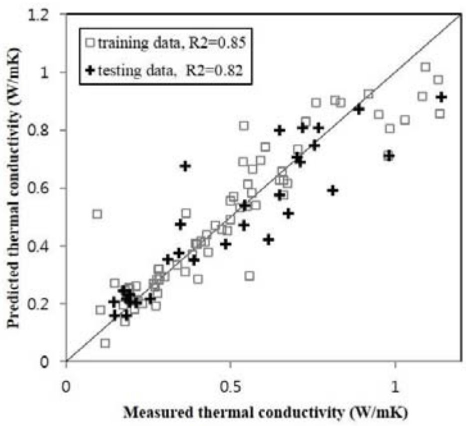


(e) R^2 by number of neuron in hidden layer



(f) Logsig(9)-Tansig model





(g) R^2 by number of neuron in hidden layer (h) Tansig(6)-Tansig model

Fig 6. Optimum number of neurons and transfer function combination

Fig 6 (a), (c), (e) and (g) show the change of coefficient of determination (R^2) and predictive value for training and testing data according to the increase in the number of neurons. As the number of neurons increased, coefficient of determination considering training data tended to increase. On the contrary, coefficient of determination for testing data which was not used in training tended to repeatedly increase and decrease rather than increase consistently. Fig (b), (d), (f) and (h) shows the comparison of predictive and experimental results considering training and testing data in case of applying the optimized number of neurons for each model. All of 4 models show high predictive value of 0.8 for the coefficient of determination (R^2) and Neural Network Model using Logsig(9)-Tansig transfer function was determined as the most reasonable model among them.

5. 4 Verification of thermal conductivity Neural Network Model

This study verified the predictive accuracy of Neural Network Model by comparing thermal conductivity obtained by 3D Curved Surface Model and Neural Network Model(Logsig(9)-Tansig). The normalized data was represented in Fig. 7 and 8. As for the 3D Curved Surface Model, the normalized average values of training data and test data were 1.079 and 1.078, respectively with the variation of 0.158 and 0.130, and the predictions became unreliable in a low range of thermal conductivity considering the dispersion. As for the Neural Network Model, „Logsig-Tansig’ transfer function combination with 9 neurons gave the highest accuracy for the estimation. The normalized average values of training data and test data were 1.006 and 0.954, respectively with the variation of 0.026 and 0.098. It can be concluded that Neural Network Model gives much more reasonable results than 3D Curved Surface Model.

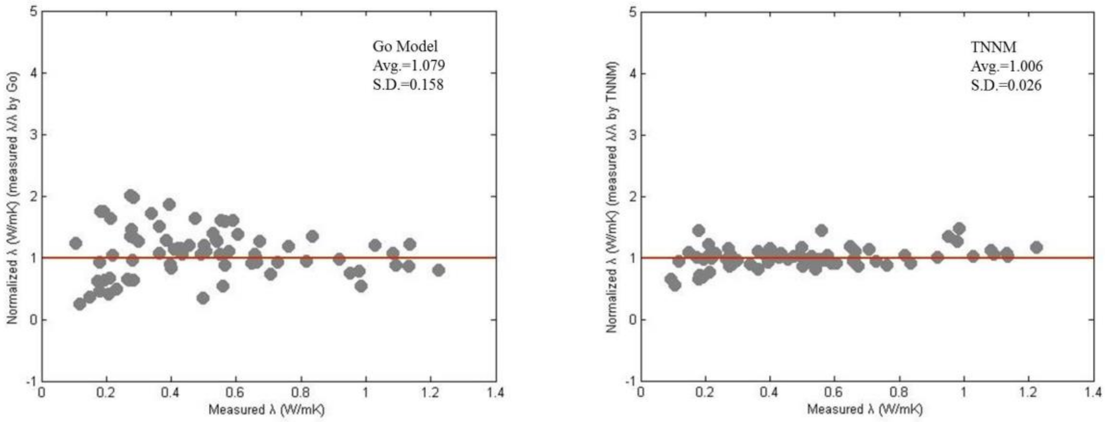


Fig 7. Comparison of normalized thermal conductivity between experimental and NNET Model results (training data)

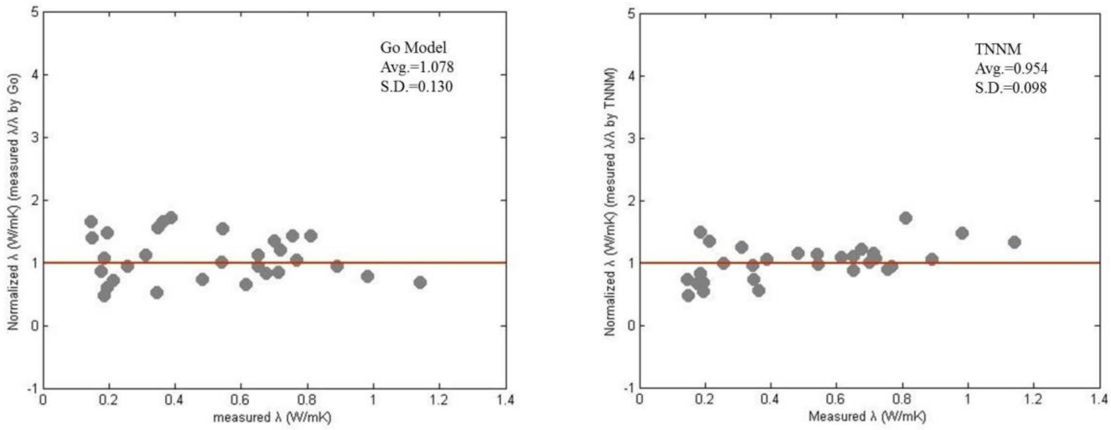


Fig 8. Comparison of normalized thermal conductivity between experimental and NNET Model results (testing data)

6. CONCLUSION

From the results obtained in this study, following conclusions can be deduced.

(1) The 3D Curved Surface model was represented as a function of porosity and water content, and the results showed that the model using only two variables can guarantee enough accuracy in prediction of thermal conductivity.

(2) As for the 3D Curved Surface Model, the predictions became unreliable in a low range of thermal conductivity considering the dispersion.
(3) As for the Neural Network Model, „Logsig-Tansig' transfer function combination with 9 neurons gave the highest accuracy for the estimation.
(4) Neural Network Model can consider diverse input parameters and hence it can show higher accuracy than other previous empirical models.
(5) Neural Network Model proposed in this study can improve its accuracy by accumulating the data and it has a great possibility in application to any types of soils in Korea.

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