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Development of a Simulation Tool for Ground Source Heat Pump Systems Using Horizontal Ground Heat Exchangers

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Abstract

Ground source heat pump (GSHP) systems have been gaining attention in recent years as a one of renewable energy utilization system, but its widespread use in Japan has been delayed due to high installation costs. The introduction of horizontal ground heat exchangers (GHEs) has a possibility to reduce the initial cost, therefore, appropriate system design is required to install the horizontal GHEs. The authors developed a simulation tool for GSHP systems using horizontal GHEs. The developed simulation tool can calculate the ground temperature surrounding the GHE, which is affected by not only the heat extraction/injection via GHEs but also the temperature change at ground surface. In addition, this tool calculates the ground temperature surrounding the GHE by superposing the temperature response, and the temperature response of the spiral coil type GHE is calculated by an applying artificial neural network (ANN). In this paper, outlines of calculation method are firstly introduced. Next, the required length of GHE was estimated as a case study using the developed simulation tool.

Keywords: Ground source heat pump system, Horizontal ground heat exchanger, Simulation tool, Artificaial neural network ;

1. Introduction

In recent years, ground source heat pump (GSHP) systems that utilize underground thermal energy, a renewable energy heat source, have been spreading in many countries as a highly efficient heat source system. However, the total installed capacity in Japan is only 0.2 GW and much smaller than North America, China and European countries [1]. The main reason is the installation costs of ground heat exchangers (GHEs). The vertical type GHE generally used in existing GSHP systems in Japan has a high initial cost of 10,000 ~ 20,000 JPY/meter for installation. On the other hand, horizontal GHEs, which utilize shallow ground several meters deep from the ground surface, requires a large site for installation, but the installation cost is much lower than that of vertical GHE. Therefore, when a large site for GHE burial is available, the adoption of horizontal GHE is expected to expand the introduction of GSHP systems due to the significant reduction in initial costs.

Horizontal GHEs can be classified into (a) Straight pipe type, (b) Spiral coil type, and (c) Comb type, as shown in Photo 1. The spiral coil GHE to be considered in this study is known to have a larger heat exchange rate per heat exchange installation area than the conventional straight pipe type because of the areal heat exchange from the top and bottom of the coil [2]. Therefore, this type of GHE system can reduce the size of the GHE burial site and the initial cost of the GSHP system. On the other hand, appropriate system design is essential for the introduction of this system. Currently, numerical calculation models for the spiral coil GHEs were developed, but it is not suitable as a design tool because of its large computational load. Although Li et al. have derived a theoretical solution to calculate the underground temperature surrounding the spiral coil GHE with a relatively small computational load [3], the computational load becomes large when the average temperature of the pipe surface is calculated.

To address this challenge, the authors have focused on artificial neural networks (ANNs), which have recently attracted attention for their application to regression and classification problems. As an example of the application of ANNs to the calculation of GHE ambient temperature field, Pasquier et al. developed an ANN model to quickly and accurately determine the short-term G-function using a model based on the thermal resistance and heat capacity [4]. The authors have also developed a regression model that reproduces the numerical results of a moving infinite cylinder problem using ANN, and have shown a fast and accurate method for calculating GHE ambient temperature in groundwater flow fields [5]. Therefore, in this study, we construct a temperature response regression model that reproduces the theoretical analysis results presented by Li et al. [3] based on the high functional representation capability of ANN and its fast computation speed, and develop a fast and accurate simulation model.

Finally, using the developed simulation tool for performance prediction, we will conduct case studies to determine the required scale of GHE.

(a) Straight pipe type (b) Spiral coil type (c) Comb type

Photo 1. Types of horizontal GHEs

2. An artificial neural network model for fast computation of temperature response of spiral coil GHE

2.1. Parameter study with theoretical solution

In order to achieve a fast calculation of the average temperature response of the spiral coil GHE, a regression model is constructed by having ANN learn the results of calculating the average temperature response with the theoretical solution. The parameters that determine the shape of the spiral coil are the loop interval *D*, the ring radius *r*, and the number of rings *N*. The input parameters to the ANN are four variables, including these three variables and the dimensionless time (Fourier number) $F_o = at/r_p^2$. In addition, a dimensionless average temperature $\Theta = \theta_{rs,mean}\lambda r_p/q_r$ was given as output for training.

In the parameter study using the theoretical solution [3], several patterns of coil geometries were prepared and the dimensionless average temperature response of the spiral coil GHE surface over 10 years was calculated at one-hour intervals. As shown in Figure 1, total of 27 patterns were studied, three patterns for each variable. The results of the calculated dimensionless temperature response are shown in Figure 2.

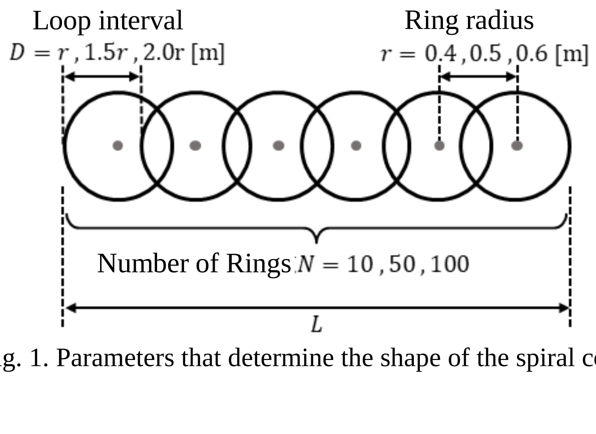

Fig. 1. Parameters that determine the shape of the spiral coil

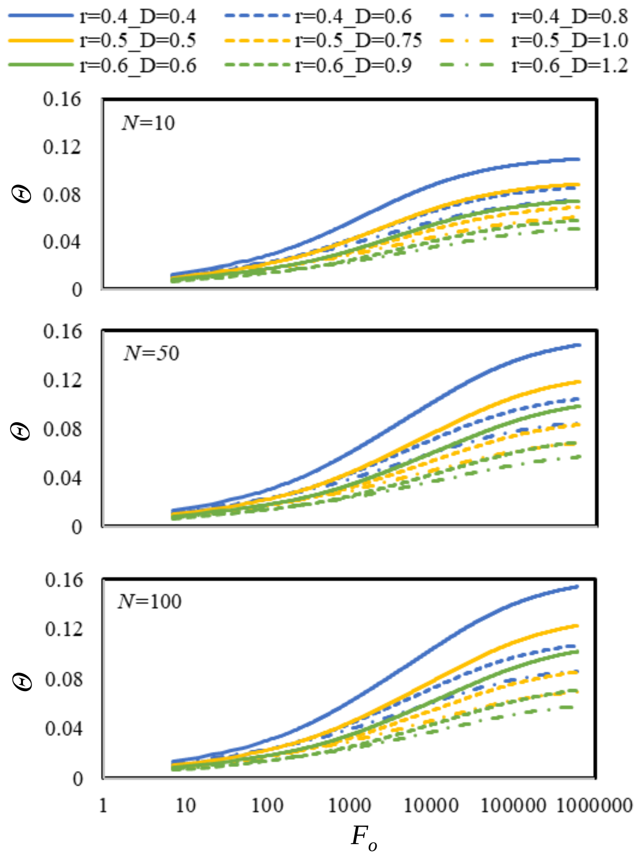

Fig. 1. Dimensionless average temperature calculated by theoretical solution

2.2. Outlines of machine learning

Figure 3 shows a diagram of the ANN. The model is a feed-forward neural network in which all units are coupled, and a ReLU function is set as the activation function in each hidden layer. In machine learning, there are hyperparameters, such as the number of hidden layers and units in ANN, that must be determined in advance during training. In this study, Bayesian optimization was used as the optimization method for hyperparameters. The hyperparameters and their search ranges are shown in Table 1. The maximum evaluation time for Bayesian optimization was 72 hours, and the maximum number of evaluations was 50. To verify the ANN performance, the dataset was randomly divided into a training dataset, a validation dataset, and a test dataset at a certain ratio of 7:1.5:1.5, respectively. The mean squared error (MSE) value was used for the loss function in the ANN learning process.

Figure 4 shows the flowchart of ANN learning. The ANN is trained on the given hyperparameter settings applying the Bayesian optimization algorithm and using the training dataset. The learned ANN is then validated using the validation dataset.

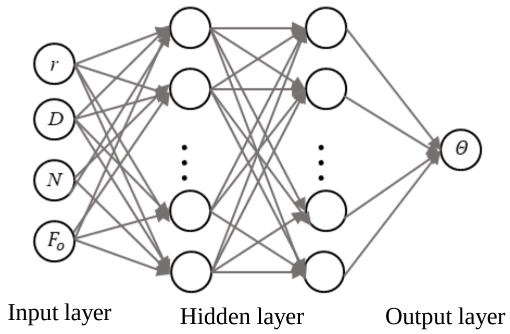

Fig. 1. A diagram of the ANN

Table 1 Hyperparameters and their search ranges

Parameter	Search range
n_{Hidden}	3-8 (Integer)
n_{Unit}	100-500 (Integer)
LR	$1.0 \times 10^{-6} – 1.0 \times 10^{-4}$
$epoch$	50-120 (Integer)
$Weight\_Decay$	$1.0 \times 10^{-12} – 1.0 \times 10^{-8}$

This is iterated within the maximum evaluation time and number of times, and the MSE for the test data is calculated for the result that finally minimizes the MSE of the verification result. The performance of the ANN is then determined.

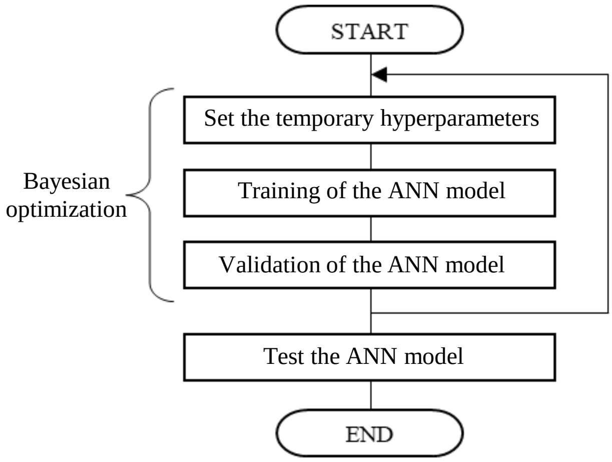

Fig. 4. A Flowchart of ANN learning

2.3. Result of machine learning

The ANN was trained in the search range of hyperparameters in the previous section. The hyperparameters that resulted in the smallest MSE as a result of Bayesian optimization are shown in Table 2. Figure 5 shows the process of determining hyperparameters by Bayesian optimization. Note that n_{Hidden}, n_{Unit}, *LR*, *epoch*, and *Weight_Decay* for each trial are shown in Figure 5 as data labels. From Figure 5, it can be seen that the parameters are updated so that the MSE becomes smaller as the number of training trials progresses.

Table 2 Hyperparameters obtained by Bayesian optimization

Parameter	Optimal value
n_{Hidden}	5
n_{Unit}	499
LR	5.74×10^{-5}
$epoch$	98
$Weight\_Decay$	2.52×10^{-12}

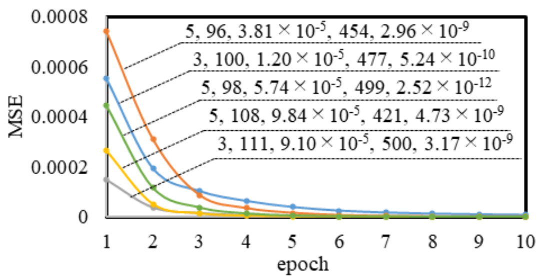

Fig.5 A process of determining hyperparameters by Bayesian optimization

Within the maximum evaluation time and number of iterations, the number of iterations was 50, and the minimum MSE was obtained at the 29th iteration. Bayesian optimization results show that the MSE for the validation data set is 1.46×10^{-9}, which is sufficiently small for a regression model. Figure 6 shows a comparison of the temperature response between the obtained ANN regression model and the theoretical solution under the condition of a ring radius of 0.4 m as an example. The MSE was 2.26×10^{-9} on average. This indicates that the constructed ANN model shows good regression performance and that the generalization performance of the learned ANN is adequate. Furthermore, a comparison of the time required for 10 years of calculations with N=100 rings shows that the ANN model takes about 2 seconds to calculate the temperature response, while the theoretical analysis takes about 20 hours, indicating that the ANN regression model significantly reduces the calculation time. This temperature response was applied to the temperature response calculation of the calculation flow shown in Figure 7, and a simulation tool was created.

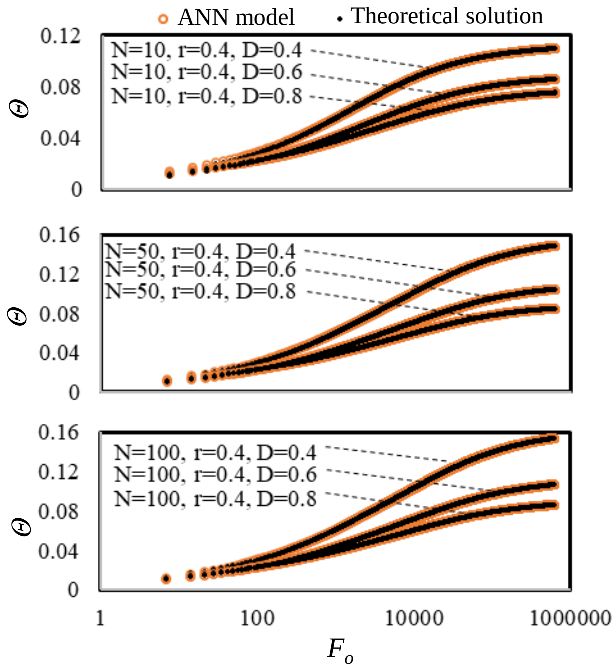

Fig. 6. Temperature response between the obtained ANN regression model and the theoretical solution

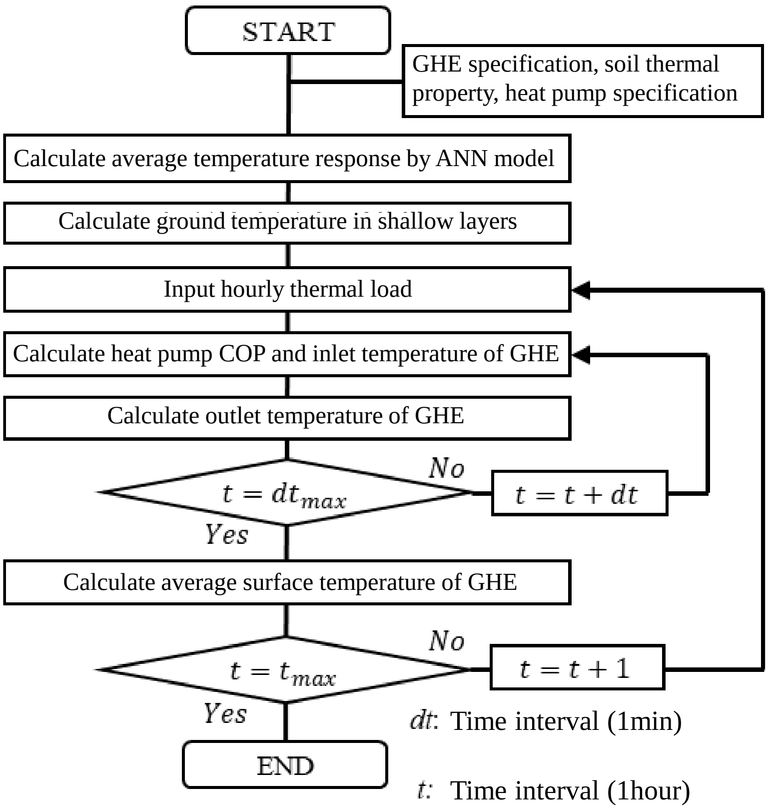

Fig.7 A calculation flowchart of simulation tool for GSHP system with spiral coil GHE

3. Case studies to determine the required scale of GHE

3.1. Calculation conditions

Using the simulation tool for the GSHP system with spiral coil GHEs described above, the GHE size required to cover the annual thermal load for a residential house is investigated. Akita and Tokyo were selected as target cities for semi-cold and moderate climate regions, respectively.

Figure 8 shows the assumed residential house. This model is assumed to have a total floor area of 116m^2 and high insulation performance. The heat loss coefficient per floor area and temperature difference is set as 1.0 W/(m^2・K) in Akita and 1.4 W/(m^2・K) in Tokyo, considering that it should be less than half that of the energy conservation standard in Japan. Air conditioning was set to operate continuously 24 hours a day, with the heating temperature set at 20ºC and the cooling temperature at 26ºC. The hourly heating and cooling load were calculated by using AE-CAD/AE-Simheat [6], which is a commercially available thermal load calculation. Figure 9 shows the hourly cooling and heating loads in annual.

The soil and GHE conditions were set as shown in Table 3. The soil effective thermal conductivity was set at 1.0 W/(m・K) and the circulation flow rate was kept constant at 20 L/min. The minimum GHE size (L in Figure 1) required to keep the fluid temperature of GHE outlet within the range of -5~35ºC throughout the year was defined as the GHE required size in each city.

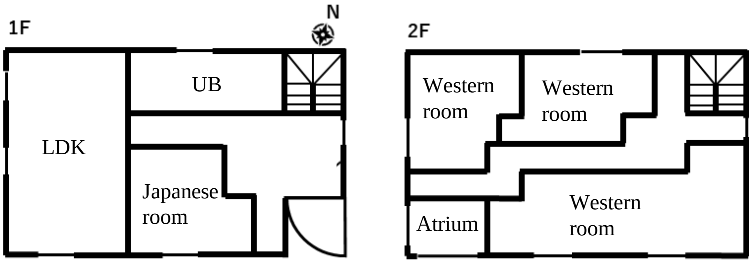

Fig. 8. The subjected residential house

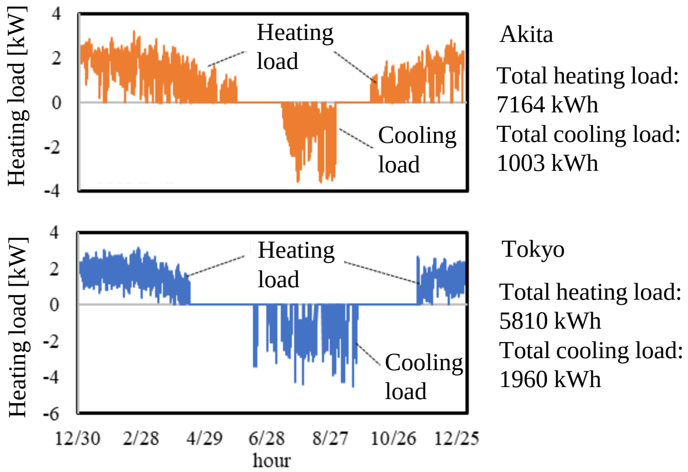

Fig. 9. Hourly heating/cooling load in annual

Table 3 Soil and GHE conditions

Soil conditions	Specific heat	2.0 kJ/(kg･K)
	Density	1500 kg/m^3
	Effective thermal conductivity	1.0 W/(m･K)
GHE conditions	Pipe inside diameter	0.025 m
	Pipe outside diameter	0.032 m
	Loop interval	0.5 m
	Ring radius	0.5 m
	Depth	1 m

3.2. Result and discussions

The minimum GHE sizes were 51 m in Akita and 60 m in Tokyo, respectively. Also, the variation of heat carrier fluid temperature of GHE outlet are shown in Figure 10 when the minimum GHE sizes were given. It was confirmed that the heat carrier fluid temperature reached the lower limit in Akita and the heat carrier fluid temperature reached the upper limit in Tokyo as a result. Based on this result, if spiral coil GHEs with a length L of 10 m are installed at intervals of 2 m, a site area of approx. 80 m^2 (= 2 m intervals × 4 × 10 m) would be required in Akita and about 100 m^2 (= 2 m intervals × 5 × 10 m) in Tokyo. While it is difficult to secure a site area in Tokyo due to the high population density, it is possible to secure a site area in Akita.

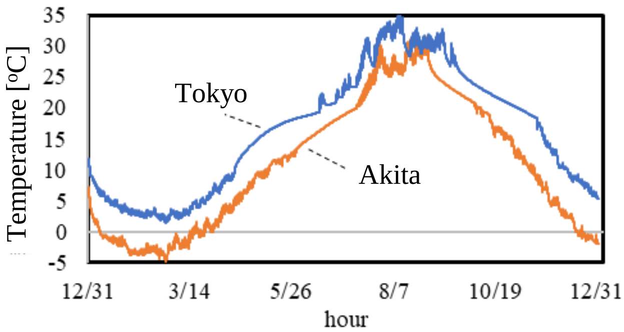

Fig. 8. The subjected residential house

4. Summary

In this study, an ANN regression model of the ambient temperature response of the ground heat exchanger was developed using the theoretical solution in order to develop a simulation tool for horizontal spiral coil type ground heat exchangers. Case studies were conducted in each city to determine the required heat exchanger length, and the following findings were obtained.

1) A regression model of the temperature response function was created by training ANN on the results of the theoretical analysis. As a result, a highly accurate regression model with an MSE of 1.46×10^{-9} was created for the validation data set. Furthermore, the ANN model required only about 2 seconds of computation time over a 10-year period with 100 number of rings, a significant reduction in the computation load.

2) The required GHEX length in each city was examined. In Akita, the required GHEX length was 51 m for the spiral coil method and 46 m for the horizontal unit method. In Tokyo, the GHEX length for the spiral coil method was 60 m and that for the horizontal unit method was 58 m. In both cities, the GHEX length for the horizontal unit method was shorter than that for the spiral coil method.

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NOMENCRATURE

a: Thermal diffusivity [m^2/s], F_o: Fourie number [-], *q*: Heat extraction rate per length [W/m], *r*: Radius [m], *t*: Time [s], θ : Temperature [ºC], Θ : Dimensionless temperature [-], λ: Thermal conductivity [W/m/K]

Subscript

p: Ground heat exchanger pipe, *r*: ring, *rs, mean*: average of ring surface