Case Study of ANN Modeling of Stratified Thermal Energy Storage and Ground Source Heat Pump Systems for Model Predictive Control

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SUMMARY
In the model predictive control (MPC) technique, prediction models are required to describe a system. Recently, artificial neural network (ANN) has been actively used to emulate physical models. However, the training structure and training data set should be carefully selected, because incorrect training may lead to errors in prediction. The purpose of this study is to verify the feasibility of ANN models for stratified thermal energy storage (TES) and borehole heat exchanger (BHE) for ground source heat pump (GSHP). Therefore, case studies were conducted for the verification of ANN models of the TES system trained by measured data and the GSHP system trained by numerical simulation results. The results showed that the coefficient of determination (R²) and the mean square error (MSE) were approximately 1 and 0, respectively, in both systems. Therefore, we expect that ANN models can be effectively utilized for accurate MPC.

1. INTRODUCTION
Recently, model predictive control (MPC) has been focused on the optimal operation of building facilities (Khakimova et al. 2017, Cole et al. 2012, Huang et al. 2015). MPC is a control algorithm that determines control inputs for a future time horizon by solving an optimization problem based on a model that represents a physical process of interest (Camacho et al. 2007). In the MPC technique, prediction models are required to describe physical processes of the target problem. However, some high-resolution physical models that are mostly based on numerical calculations usually require high computation costs. Considering the intrinsic nature of optimization problems that have iterative calculation processes, reducing the computation time while maintaining accuracy is an important issue.

Recently, artificial neural network (ANN) models have been actively used to emulate physical models (Afram et al. 2017; Afram et al. 2014; Norgaard et al. 2000). Compared to a high-resolution mathematical model that describes a complex physical phenomena, the ANN model has lower computation cost for one execution. However, in using the ANN model, the researcher’s know-how of designing a training structure and method of ANN model is the most effective factor so far. Also, the final model is supposed to be chosen depending on the researchers’ experience in accordance with their research subject and purpose. For these reasons, the training structure and method of the data set should be constructed through sufficient trial and error, because incorrect training may lead to errors in prediction.

Therefore, the purpose of this study is to verify the feasibility of ANN models for the prediction in a stratified thermal energy storage (TES) and borehole heat exchanger (BHE) for a ground source heat pump (GSHP). For the stratified TES system, the feasibility of the ANN model was verified through case studies of the neural networks trained by the measured data. For the GSHP system, verification of the feasibility of ANN was performed by the same process through case studies of the neural networks trained from numerical simulation results. Simulation of the BHE was carried out using a fully discretized 3D numerical model based on the finite element method.

2. METHODS
2.1. Stratified TES System
2.1.1. Training Data Set
In the case of the stratified TES system, the actual operating data of a building located in Tokyo was utilized as training data for the ANN model. Using the actual operating data of the building can overcome the drawbacks that could be overlooked in the modeling process of the physical system, such as errors from the model discrepancy between a mathematical model and actual physical phenomena, which cannot be considered simply by a heat balance equation and needs a lot of effort to correct.

The utilized training data were referred from the actual operating data of a building with a stratified chilled water TES unit with a total volume of 2,800 m³. The measurement period was 1 year from January 1, 2016, to December 31, 2016, measured at an interval of every 10 min. The measurement points were a total of 20 nodes in the vertical direction inside the stratified TES tank. The total number of effective measured data points is 51,913, since 643 data points were lost during the measurement. In this study, the hourly measured 8,653 data points were used as a training data set,
excluding lost data. A schematic outline of this stratified chilled water TES system is shown in Figure 1. When the TES system is operated in charging mode, the inlet water temperature \(T_c\) from the heat source is 4 °C. When the TES system is operated in discharging mode, the return water temperature \(T_r\) of TES from the load side is 14 °C. In addition, the top layer of the TES is denoted as node 1 and the bottom layer of the TES as node 20.

### 2.1.2. ANN Modeling

In this study, the ANN model was created using a neural network toolbox based on MATLAB R2017a®. The Levenberg-Marquardt (LM) algorithm, which is commonly used for training ANN models, was used as an optimization method. Out of the whole data set including input data and target data, 70% of the data were used for neural network training, and 15% for verification to prevent excessive learning such as over-fitting, the remaining 15% were used to evaluate the ANN models and were not involved in the training and verification process.

The ANN model was developed to predict how the temperature distribution of the bottom layer and all 20 layers of the TES tank changes, on the basis of the measured temperature and the amount of heat calculated from the total TES volume of 2.800 m³. The structure of the ANN model was selected as a four-layer feedforward structure with two hidden layers (input-hidden-hidden-output). Each hidden layer had 20 neuron nodes.

### 2.1.3. Case Study

In order to verify the feasibility of the ANN model of the stratified TES system, we studied two cases according to the composition of input data and target data. In Case 1, the training data were organized to predict the outlet temperature of the current time step \(T_{20}^{t}\) by the remaining heat amount, the outlet temperature of the previous time step \(\bar{T}_{20}^{t-1}\), and the predicted remaining amount of the current time step \(\bar{Q}_{20}^{t}\). In Case 2, the training data were organized to predict the temperature of all 20 layers of the current time step \(T_{i}^{t}\) by the temperature of all 20 layers and the remaining heat amount of the previous time step \(Q_{i}^{t-1}\).

Case 1 can be utilized to predict the outlet temperature (the temperature of the 20th layer), which should be sent to the load side in chilled-water TES operation. Case 2 can be used to analyze the whole distribution of the temperature stratification in a more detailed manner, not only the outlet temperature. Table 1 shows the organized conditions of the training data parameters in Case 1 and Case 2.

### 2.2. BHE for GSHP System

#### 2.2.1. Training Data Set

In the case of the BHE for GSHP system, the results of the numerical simulation were used as training data for the ANN model creation. Simulation of the BHE was carried out using a fully discretized 3D numerical model based on the finite element method. The simulation software tool FEFLOW 7.0® was used. The details of the Numerical simulation based on the finite element method has the advantage of high accuracy in prediction, but it has the disadvantage of high computational load from creation of the geometry and mesh to obtain calculation results. Therefore, as an alternative to the computational load reduction, the feasibility of using the numerical simulation results as the training data of the ANN model was examined in this study. Numerical modeling details and its validation process against the experimental data can be found in Choi and Ooka (2016).

For thermal conductivity analysis under the ground, the infinite line source (ILS) model is actively used these days (Carslaw et al. 1959; Ingersoll et al. 1954). However, in using this model, it is assumed that the BHE is a linear heat source, so that the heat transfer between the circulating water at the BHE wall area is simplified by using the steady-state thermal resistance without considering the heat capacity of the BHE itself. Therefore, the calculation results of short-term change are not guaranteed to be accurate, because the temperature response to dynamically changing thermal loads is either overestimated or underestimated. On the other hand, the numerical simulation based on the finite element method has an advantage in that it can reproduce the temperature response characteristics of the actual BHE, because the calculation is performed considering the shape and heat capacity of the BHE itself. However, because it has quite a large calculation load, the simulation results were used as training data for ANN modeling to reduce the computational cost.

#### Geometry

The shape of the ground and BHE analyzed in numerical simulation is shown in Figure 2. The ground was set to 60 m in length, 60 m in width, and 150 m in depth. The height of the BHE was 100 m. The radius of borehole was 0.062 m, the radius of U-tube was 0.013 m, the pipe thickness was 0.003 m, and the center distance between the inlet and outlet of the U-tube was set to 0.056 m. As a result of generating a geometry and mesh elements, the total number of mesh elements is 767,084.

#### Boundary Condition

All the boundary conditions assigned to the numerical model are listed in Table 2. The surface of the top layer was set as Adiabatic. A Dirichlet condition of 17 °C was assigned to lateral and bottom surfaces. U-tube legs were modelled using a 1D linear element. The details can be found in Choi and Ooka (2016). In addition, a time-varying Dirichlet condition was assigned to BHE inlet element according to Equation (1) which will be described in the next section. In Table 2, the negative and positive signs for well-type boundary condition represent the inflow and outflow to the numerical model domain, respectively. Furthermore, the initial temperature of the whole model domain was set to 17 °C.

#### Table 1. Input and target data parameters for training the ANN model of a TES system

<table>
<thead>
<tr>
<th>Case</th>
<th>Input data</th>
<th>Target data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>(Q_{1}^{t-1}, Q_{2}^{t-1}, \ldots, Q_{20}^{t-1})</td>
<td>(T_{20}^{t})</td>
</tr>
<tr>
<td>Case 2</td>
<td>(Q_{1}^{t-1}, T_{1}^{t-1}, \ldots, T_{20}^{t-1})</td>
<td>(T_{1}^{t}, \ldots, T_{20}^{t})</td>
</tr>
</tbody>
</table>

#### Table 2. Boundary conditions of numerical model

<table>
<thead>
<tr>
<th>Type</th>
<th>Condition</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top</td>
<td>Surface</td>
<td>Adiabatic</td>
</tr>
<tr>
<td>Lateral</td>
<td>Surface</td>
<td>Dirichlet</td>
</tr>
<tr>
<td>Bottom</td>
<td>Surface</td>
<td>Dirichlet</td>
</tr>
<tr>
<td>BHE inlet</td>
<td>Linear element</td>
<td>Dirichlet</td>
</tr>
<tr>
<td>BHE outlet</td>
<td>Linear element</td>
<td>Well-type</td>
</tr>
</tbody>
</table>

The simulation results were used as training data for the ANN model as well as the numerical modeling details and its validation process against the experimental data can be found in Choi and Ooka (2016).
Calculation Condition

The calculation condition for the numerical simulation is described in Equation (1), which is used to calculate the inlet temperature of the BHE inflow at the current time step. In this study, the numerical simulation was performed considering the heating operation mode. The sign of the second term on the right-hand side in Equation (1) is negative when the GSHP operates in heating mode. When the operating mode is cooling, the sign of the second term in Equation (1) is positive. However, in this study, the heating operation mode was examined only.

The equation (1) describes the boundary condition of U-tube inlet. The inlet fluid temperature of BHE at the current time step \( T_{\text{in}}^t \) is determined by retrieving the outlet fluid temperature at the previous time step \( T_{\text{out}}^{t-1} \) and a heat rate at current time step \( Q_{\text{BHE}}^t \) which is transferred from the GSHP to the circulating fluid. The material properties of the soil, grout, pipe, and circulating fluid used in the calculation were summarized in Table 3, and the calculation time step was set to a 1-hour interval.

\[
T_{\text{in}}^t = T_{\text{out}}^{t-1} \pm \frac{Q_{\text{BHE}}^t}{pc\dot{V}} \tag{1}
\]

- \( T_{\text{in}}^t \): Inlet temperature of BHE at current time step, \( t \) [°C]
- \( T_{\text{out}}^{t-1} \): Outlet temperature of BHE at previous time step, \( t-1 \) [°C]
- \( Q_{\text{BHE}}^t \): Heat rate injected(+) or extracted(-) at current time step, \( t \) [W]
- \( p \): Density of water [kg/m³]
- \( c \): Specific heat capacity of water [J/(kg K)]
- \( \dot{V} \): Volumetric flow rate of water [m³/s]

### Table 3. Material properties used in numerical simulation

<table>
<thead>
<tr>
<th>Material</th>
<th>Volumetric flow rate [MJ/(m³ K)]</th>
<th>Heat conductivity [W/(m K)]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil</td>
<td>2.6</td>
<td>1.8</td>
</tr>
<tr>
<td>Grout backfill</td>
<td>2.1</td>
<td>1.8</td>
</tr>
<tr>
<td>Pipe</td>
<td>1.8</td>
<td>0.45</td>
</tr>
<tr>
<td>Pseudo-fluid in U-tube</td>
<td>1x10⁻⁶</td>
<td>1000</td>
</tr>
</tbody>
</table>

Demand Load Data

The extracted BHE heat rates were randomly generated to ensure the diversity of the training data. The data were prepared for 110 weeks on a weekly basis with every 1 hour intervals, and therefore, the total number of data points was 18,480 (24x7x110). The calculated data obtained by substituting the 18,480 data points into the numerical simulation were used as the training data set of the ANN model.

In addition, assuming that the initial temperature of the ground was 17 °C, the training data corresponding to the change from the initial ground temperature was insufficient when the data of 110 weeks was calculated all at once. Thus, the simulation was calculated by dividing the data into 10-week intervals. Figure 3 shows an example of 10 weeks of randomly generated extracted heat rate patterns. In addition, Figure 4 shows the simulation results of BHE inlet temperature and outlet temperature, calculated with the 10-week heat amount pattern described in Figure 3.

#### 2.2.2. ANN Modeling

For the ANN modeling of the BHE for GSHP system, the MATLAB R2017a® neural network toolbox was used, and the LM algorithm was used as an optimization method as well as the TES system. The structure of the ANN model was a three-layer (input-hidden-output) feedforward type in all cases (Case 3 – Case 10). The number of nodes in the hidden layer was 10 neuron nodes in all cases.
2.2.3. Case Study

In the ANN modeling of the BHE for GSHP system, the purpose of the case study was to examine the composition of the various input data to predict the BHE outlet temperature at the current time step. The prediction accuracy of the BHE outlet temperature for the ANN model was investigated by different input data conditions in each case. The specific input data conditions for each case are shown in Table 4.

The parameters used in the composition of the input data are mainly: 1) The outlet temperature of the BHE \( T_{\text{out}}^t [\degree \text{C}] \), 2) the extracted heat rate from the BHE \( (Q_{\text{BHE}} [\text{kWh}]) \), 3) the cumulative extracted heat amount to the BHE \( (\Delta Q_{\text{BHE}} [\text{W}]) \), and 4) the extracted heat rate difference between the current time step and the previous time step \( (\Delta Q_{\text{BHE}}^t [\text{W}]) \). Eight cases were considered in a combination of the parameters of the current time step \( (t) \) and the previous time step \( (t-1) \) from the current time step. The target data was unified as the BHE outlet temperature at the current time step \( (t) \) for all eight cases.

3. RESULTS

Table 5 shows the results of all 10 cases of the TES system and the BHE system. Figure 5 compares the ANN model results among the all cases for the TES system and the BHE for GSHP system.

Table 4. Input and target data parameters for training the ANN model of the BHE system

<table>
<thead>
<tr>
<th>Case</th>
<th>Input data</th>
<th>Target data</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>( T_{\text{out}}^{t-1}, T_{\text{out}}^{t-2}, Q_{\text{BHE}}^{t-1} )</td>
<td>( T_{\text{out}}^t )</td>
</tr>
<tr>
<td>4</td>
<td>( T_{\text{out}}^{t-1}, Q_{\text{BHE}} )</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>( T_{\text{out}}^{t-1}, T_{\text{out}}^{t-2}, Q_{\text{BHE}} )</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>( T_{\text{out}}^{t-1}, Q_{\text{BHE}}^{t-1} )</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>( T_{\text{out}}^{t-1}, Q_{\text{BHE}}^{t-1}, Q_{\text{BHE}} )</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>( T_{\text{out}}^{t-1}, T_{\text{out}}^{t-2}, Q_{\text{BHE}}^{t-1} )</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>( T_{\text{out}}^{t-1}, \Delta Q_{\text{BHE}} )</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>( T_{\text{out}}^{t-1}, \Delta Q_{\text{BHE}}^{t-1} )</td>
<td></td>
</tr>
</tbody>
</table>

Table 5. Results of average value after five training runs in all 10 cases of the TES system and BHE for GSHP system

<table>
<thead>
<tr>
<th></th>
<th>( R^2 )</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>0.9978</td>
<td>0.0005</td>
</tr>
<tr>
<td>Case 2</td>
<td>0.9936</td>
<td>0.0325</td>
</tr>
<tr>
<td>Case 3</td>
<td>0.9953</td>
<td>0.0097</td>
</tr>
<tr>
<td>Case 4</td>
<td>0.9877</td>
<td>0.0254</td>
</tr>
<tr>
<td>Case 5</td>
<td>0.9870</td>
<td>0.0267</td>
</tr>
<tr>
<td>Case 6</td>
<td>0.9931</td>
<td>0.0140</td>
</tr>
<tr>
<td>Case 7</td>
<td>0.9942</td>
<td>0.0118</td>
</tr>
<tr>
<td>Case 8</td>
<td>0.9945</td>
<td>0.0114</td>
</tr>
<tr>
<td>Case 9</td>
<td>0.9645</td>
<td>0.0717</td>
</tr>
<tr>
<td>Case 10</td>
<td>0.9907</td>
<td>0.0198</td>
</tr>
</tbody>
</table>

![Figure 5. Comparison of average values of the results after five training runs between all 10 cases of the TES system and BHE for GSHP system](image)

![Figure 6. Linear regression between target temperature and predicted temperature of Case 1 which is shown closest to the average \( R^2 \) value (0.9981) during the five times training](image)

![Figure 7. Error histogram between target temperature and predicted temperature of Case 1 which is shown closest to the average MSE value (0.0004) during the five times training](image)

![Figure 8. Linear regression between target temperature and predicted temperature of Case 3 which is shown closest to the average \( R^2 \) value (0.9958) during the five times training](image)
cases of the BHE for GSHP system. The MSE had the lowest value of 0.0097. This means that using the input data with the previous outlet temperature and current extracted heat rate \((T_{\text{out}}^{-1}, \dot{Q}_{\text{BHE}}^t)\) and the temperature of two-steps-previous time step and extracted heat rate of previous time step \((T_{\text{out}}^{-2}, \dot{Q}_{\text{BHE}}^{t-1})\) from the BHE is the most accurate model to predict the outlet temperature at the current time step \((T_{\text{out}}^{t})\). During the five times training process, the fourth one was closet to the total average value, where the R² and MSE value were 0.9958 and 0.0088, respectively as described in Figure 8 and Figure 9.

Case 4

Case 4 is a model that uses the outlet temperature at previous time step and extracted heat rate of current time step \((T_{\text{out}}^{-1}, \dot{Q}_{\text{BHE}}^t)\) as input data. Because there is a lack of information about extracted heat rate at previous time step, it was expected that the accuracy of the model would be lower than that of Case 3. However, the results showed that the average MSE value was as high as 0.0254.

Case 5

In the ANN model of Case 5, the parameter of the outlet temperature at the two-steps-previous time step \((T_{\text{out}}^{-2}, \dot{Q}_{\text{BHE}}^{t})\) is added in input date of Case 4. It can be considered that this model can indirectly learn how the extracted heat rate changes at every time steps, but the result was quite different from the result of Case 4. This means that it is difficult to understand the unknown variation under the ground without sufficient information.

Case 6

In Case 6, the parameter of the extracted heat rate at the previous time step \((\dot{Q}_{\text{BHE}}^{t-1})\) is added to the input data of Case 4. In terms of accuracy, the average value of R² was 0.9931, and the average value of MSE was 0.0140. Both results were better than those of Case 4 and Case 5.

Case 7

In Case 7, the parameter of the cumulative extracted heat amount until current time step \((\dot{Q}_{\text{BHE}}^{t})\) is added to the input data of Case 4. As a result, the average value of R² was 0.9942, and the average value of MSE was 0.0118. Both the R² and the MSE value were worse than those of Case 4. This means that the parameter of the cumulative extracted heat amount is not an important parameter to be considered as training data for predicting the outlet temperature of the BHE system.

Case 8

In Case 8, the parameter of the cumulative extracted heat amount until the current time step \((\dot{Q}_{\text{BHE}}^{t})\) was added to Case 5. The value of R² was 0.9945, and the value of MSE was 0.0114. Both R² and MSE values were positioned in the middle accuracy among all cases.

Case 9

In Case 9, the parameter of the extracted heat rate difference between the current time step and previous time step \((\Delta Q_{\text{BHE}}^{t})\) was additionally considered. However, the result of Case 9 was the worst out of all cases for emulating the BHE system. For this reason, we found that the extracted heat rate difference \((\Delta Q_{\text{BHE}}^{t})\) is not a valuable parameter as training data for the ANN model of the BHE system.

Case 10

Like Case 9, Case 10 includes the parameter of the extracted heat rate difference. However, In Case 10, the extracted heat
rate difference between the previous time step and two-steps-

previous time step \((\Delta Q_{BHE}^{t-1})\) is added as well as the outlet
temperature at the two-steps-previous time step \((T_{out}^{t-2})\) as an
input data parameter. As a result, the average value of \(R^2\) was
0.9907, and the average value of MSE was 0.0198,
representing a large improvement compared to Case 9.

4. DISCUSSION

As a result of examining 10 cases, including two cases of the
stratified chilled water TES system and eight cases of the BHE
for GSHP system, it is considered that the main parameter of
training data when creating the ANN model of each plant is as
follows.

- In the case of the stratified chilled water TES system,
  the parameter of remaining heat amount at the
current and previous time step \((Q^{t-1}, Q^{t})\) and outlet
temperature at the previous time step \((T_{out}^{t-1})\) are valid
  as input data for estimating the outlet temperature \((T_{out}^{t})\)
to be sent to the load side.

- In the case of the BHE for GSHP system, the
  information of outlet temperature of the two-steps-
  previous time step and previous time step \((T_{out}^{t-1}, T_{out}^{t})\)
  and the extracted heat rate of the current time step
  and previous time step \((Q_{BHE}^{t}, Q_{BHE}^{t-1})\) are necessary
  parameters for creating the ANN model with higher
  prediction when obtaining the predicted outlet
  temperature at the current time step \((T_{out}^{t})\).

- A parameter of extracted heat rate difference
  between the current and previous time step \((\Delta Q_{BHE}^{t})\).
is considered to be unsuitable as ANN training
  information for predicting the borehole outlet
temperature.

- It is possible to create an ANN model using the
  numerical simulation results for the BHE system.

- If there is an unknown parameter that is necessary to
  predict for the control, an ANN model can be created
  and utilized with a verification process in composition
  of input and target data parameters.

- Furthermore, the created ANN model, which
  represents the plant system, can be utilized for the
  MPC algorithm.

5. CONCLUSIONS

In this study, ANN models of the stratified chilled water TES
and BHE for GSHP systems were created by conducting a
case study. In the process of modeling the ANN, actual
operating data were used as a training data set for the TES
system. For the BHE system, the ANN model was developed
by using the results of numerical simulation. We studied how
to construct a training data set through two case studies of the
TES system and eight case studies of the BHE system. As a
result, it is confirmed that an ANN model with high accuracy
can be constructed by combining appropriate input data
parameters. The research will continue to investigate whether
it is possible to control the systems efficiently by applying an
ANN model to the MPC algorithm.

ACKNOWLEDGEMENT

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Heating, Air-conditioning and Sanitary Engineers of Japan.

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