Optimization of operation times of a heating system in office building
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ABSTRACT
A method is proposed for optimizing the operation times of a heating system in an office building for saving energy. The method involves determining the optimal start and stop times of the heating system by using an optimized artificial neural network (ANN) model, which was developed in this study. A program based on back-propagation learning was used for ANN learning. Furthermore, the amount of initial learning data, the optimal time interval for measuring the input data and the acceptable error for the practical application of the ANN model to real buildings were determined from the results of a daily simulation performed using the optimized ANN model integrated with a program for room air temperature prediction. An evaluation of the ANN’s performance in determining the optimal start and stop times of a building heating system for unexperienced learning data showed its potential to save energy.

1. Introduction
In Korea, it is becoming increasingly important to save energy because of the country’s high dependence on foreign energy sources, global warming due to the use of fossil energy, and the 37% reduction target for business-as-usual greenhouse gas emissions to be achieved by 2030. The building sector accounts for about 24% of the total energy consumption (Yang 2010). In particular, actual measurements of office building (Industry Academic Cooperation Foundation of Ewha Womans University 2018) have shown that HVAC equipments such as heating and cooling systems account for about 54.9% of a building’s energy consumption, and heating systems in office buildings consume more than the energy consumed by cooling systems as shown in Figure 1. This indicates the high energy-saving potential of these systems.

Accordingly, a strategy for reducing heating energy consumption is required. One way to save energy while providing a comfortable environment for the occupants during the operation times of the building is to reduce the operation time of the HVAC system and to actively use natural energy. Figure 2 shows several control methods; it is possible to shorten the operation time of the heating system by optimizing its start and stop times and controlling its duty cycle.

Figure 3 shows room air temperature changes during heating in a typical office building with a regular occupancy schedule. The set-point room air temperature \( T_{sp} \) must be maintained by a controller during occupied times. However, during unoccupied times, it is not necessary to maintain the set-point temperature, and therefore, the heating system can be turned off.

If the heating system is turned on at \( t_1 \), and the room air temperature is increased to be within the comfort range before \( t_2 \), energy is wasted, and if it reaches the comfort range after \( t_2 \), the occupants will be uncomfortable. Furthermore, if the heating system is turned off at the end time \( t_e \) of occupancy, the room air temperature is maintained within the throttling range for a certain period of time after the occupied times because of the heat capacity of the building, so unnecessary energy can be used.

As the indoor air temperature depends on many parameters, such as the outdoor air temperature, building structure, and equipment capacity, on the basis of a consideration of the thermal characteristics of the building and equipment, the heating system should be turned on at \( t_s \), which is determined such that the target temperature is reached at \( t_2 \), at which instant automatic control takes over. In this way, owing to the delay (due to thermal inertia and the aforementioned heat capacity) in the temperature reduction, the room air temperature can be maintained within a comfortable range even if the heating system is turned off before the end of the occupancy. When the heating system is turned off, the room air temperature falls. When the room air temperature reaches the minimum set-point temperature \( T_{sp} \), since any further fall can cause freezing or condensation, the controller should start the heating system to protect the equipment and maintain the minimum set-point temperature.
For the optimization of the operation times of the heating system for saving energy, it is essential to determine the optimal start and stop times of the heating system, and the most important factor for this is determining the correct $t_1$ and $t_3$. Previous studies (Park 1983; Levermore 2000; Seem 1989; Korea Institute of Construction Technology 1987) on the determination of the start and stop times have considered several parameters such as the indoor and outdoor air temperatures and the supplied heat capacity, and mathematical solutions such as recursive equations have also been applied (Tae 1992).

The control loop of a heating system, which determines the start and stop times, is strictly not linear, and the system characteristics change every year. Moreover, the thermal response of the building also varies. Consequently, the aforementioned parameters become dynamic, and the accurate determination of the start and stop times becomes difficult. Therefore, it becomes necessary to use the concept of "learning," which involves the use of previous operation data of the system, to determine the relationship between the input and output of the HVAC system (Nobuo 1982; Trane Inc. 1990).

An artificial neural network (ANN) model can be used to solve a problem through learning. An ANN model is based on the information processing method employed by the human brain, and learning is based on data accumulated in the past. In addition, an ANN-based control system has the unique capability to learn online, facilitating the application of highly flexible control methods. ANNs have been successfully used in similar applications and many other applications, such as control of equipment (Curtiss 1992; Ben-Nakhi and Mahmoud 2002; Moon 2012; Chung et al. 2017; Li et al. 2013; Lee, Yeo, and Kim 2002; Moon, Lee, and Kim 2014; Dai et al. 2019; Yang et al. 2018). In previous studies (Yang 2010; Yang, Yeo, and Kim 2004), their applicability to the determination of the

![Figure 1. Site energy intensity (kWh/m$^2$ year) of office building in Korea.](image1)

![Figure 2. Various operation control methods for energy saving in office buildings.](image2)

![Figure 3. Concept of optimal operation times.](image3)
optimal start and stop time of heating and cooling equipments has been confirmed. In this study, an ANN model that could be used for determining the optimal start and stop times of a building heating system was developed and its performance was evaluated. Furthermore, the parameters involved in the operation of a control system in a real building were optimized, and the energy-saving effect of the optimal start and stop control of the heating system was analyzed through a simulation.

2. Development of simulation model for optimization of operation times

2.1. Program for ANN algorithm

The basic principle of the error back-propagation learning (Hertz, Kroog, and Palmer 1991), which was the ANN learning technique used in this study, is as follows.

If input patterns are provided to each unit of the input layer, the input signal is converted in each unit, transferred to the intermediate layer, and finally output from the output layer. The connection weight is adjusted to the direction of reducing the difference by comparing the output value with the expected value, and it is adjusted again on the basis of the backward propagation in the upper layer. In the back-propagation learning technique, a two-layer neural network is extended to a neural network having three or more layers, including an intermediate layer, and the technique is also called generalized delta rule.

Figure 4 shows the error back-propagation process in the generalized delta rule. First, when the neural network operates on a given input pattern and outputs it, errors in the output layer neurons are obtained. The value obtained by subtracting the active value of the output neuron from that for the target pattern is the error of the output neuron. In Figure 4, $e_5$, $e_6$, and $e_7$ are the errors of output neurons.

The equation for obtaining delta $j$ of the output layer neurons from the error of the neurons is as follows:

$$\delta_j = f'(net_j) \cdot e_j = \frac{\partial f(net_j)}{\partial net_j} \cdot e_j = a_j(1 - a_j) \cdot (t_j - a_j)$$  \hspace{1cm} (1)

where $e_j$ is the error of output layer neuron $j$; $a_j$ is the activation value of hidden layer neuron $j$; $t_j$ is the component of the target pattern corresponding to the output layer neuron $j$.

Once the errors of the hidden neurons are obtained, delta $i$ of the hidden neurons and error can be obtained from the following Equations (2) and (3):

$$\delta_i = f'(net_i) \cdot e_i = \frac{\partial f(net_i)}{\partial net_i} \cdot e_i = a_i(1 - a_i) \cdot e_i$$  \hspace{1cm} (2)

$$e_i = \sum_j \omega_{ij} \delta_j$$  \hspace{1cm} (3)

where $e_i$ is the error of hidden layer neuron $i$; $a_i$ is the activation value of hidden layer neuron $i$; $\omega_{ij}$ is the connection weight from neuron $i$ to neuron $j$.

The adjustment of the connection weight between neurons is done using the following Equation (4):

$$\omega_{(new)}_{ij} = \omega_{(old)}_{ij} + \alpha \delta_j a_i$$  \hspace{1cm} (4)

where $\omega_{(new)}_{ij}$ is the connection weight after adjustment between neurons $i$ and $j$; $\omega_{(old)}_{ij}$ is the connection weight before adjustment between neurons $i$ and $j$; $\alpha$ is the learning rate.

Figure 5 shows the architecture of the ANN simulation program based on back-propagation learning. At each measurement point, data is entered into the ANN, and the optimal start and stop times for each measurement time interval are calculated by ANN recall.

2.2. Thermal model for calculation of room air temperature

2.2.1. Synopsis of prediction of room air temperature

It is necessary to obtain as accurate and as much sample data as possible for obtaining a solution through the learning of neural networks. A good way to obtain such data is to source data from the actual building to which the solution is to be applied. In this study, for the calculation of the optimal start and stop

Figure 4. Schematic architecture of back-propagation learning.

Figure 5. Architecture of the ANN simulation program.
times with the ANN model, it was necessary to optimize the model by using a large amount of learning data corresponding to various conditions. However, for the development of an ANN model that is applicable to various buildings, data collected from an actual building are insufficient. Therefore, a program to simulate various variables and generate learning data was required. Accordingly, a room air temperature prediction program was developed for generating learning data for various conditions.

The main function of the program was to print a normalized output, such as the time taken to reach the target temperature when heat is supplied to a room, the time from which the room air temperature is maintained within the throttling range of the temperature controller when the heating system is stopped, the outdoor air temperature, the outdoor air variation rate, the room air temperature, and the room air temperature variation rate at the start and stop times of the heating system.

2.2.2. Calculation of room air temperature
In this study, for the prediction of the room air temperature, an analytical model based on the finite difference method (Incropera and DeWitt 1990) was developed by considering a unit space with windows for the full consideration of the heat transfer characteristics of the air-conditioned space.

Figure 6 shows the indoor air model used for calculating the room temperature. There is convection heat exchange between the inside wall surface and the room air, and between thermal contents such as furnishings and the room air. The room air temperature is determined by parameters such as the surface temperature of each wall, the convection coefficient of the walls, the rate of infiltration, the rate of air supply, and the internal heat gain from people, lighting, equipment, etc. The thermal equilibrium Equation (5) indicates the convection heat transfer from the wall surface and thermal materials, indoor heat gain, and infiltration. The room air temperature can be calculated in the next time step \( \rho_{air}C_{air} \frac{\Delta T_{air}}{\Delta t} = \sum_{s=1}^{n} h_s A_s (T_{s} - T_{air}) + h_r A_r (T_{r} - T_{air}) + \rho_{air}C_{air} V_{supply} (T_{supply} - T_{air}) + \rho_{air}C_{air} V_{infil} (T_{out} - T_{air}) + (q_{c,p} + q_{c,J} + q_{c,e}) \)

\[ (5) \]

In Equation (5), \( \rho_{air} \) is the air density, \( \text{kg/m}^3 \); \( C_{air} \) is the specific heat of air, \( \text{J/kg}^\circ\text{C} \); \( V_{air} \) is the room volume, \( \text{m}^3 \); \( T_{air} \) is the room air temperature, \( ^\circ\text{C} \); \( \Delta t \) is the calculation time interval, sec; \( n \) is the number of wall; \( h_s \) is the convection heat transfer coefficient for surface of wall \( s \), \( W/m^2\circ\text{C} \); \( A_s \) is the surface area of wall, \( \text{m}^2 \); \( T_{s} \) is the surface temperature of wall \( s \), \( ^\circ\text{C} \); \( A_r \) is the surface area of thermal contents, \( \text{m}^2 \); \( h_r \) is the convection heat transfer coefficient for surface of thermal contents, \( W/m^2\circ\text{C} \); \( T_{r} \) is the surface temperature of thermal contents, \( ^\circ\text{C} \); \( V_{supply} \) is the rate of air supply, \( \text{m}^3/\text{sec} \); \( T_{supply} \) is the supply air temperature, \( ^\circ\text{C} \); \( V_{infil} \) is the rate of infiltration, \( \text{m}^3/\text{sec} \); \( T_{out} \) is the outdoor air temperature, \( ^\circ\text{C} \); \( q_{c,p} \) is the convective component of sensible heat gain from people, \( W \); \( q_{c,J} \) is the convective component of sensible heat gain from lighting, \( W \); \( q_{c,e} \) is the convective component of sensible heat gain from equipment, \( W \).

Also, as shown in Figure 7, conduction heat exchanges occur between the inside surfaces and the interiors of walls, convection heat exchange occurs between the inside wall surface and the room air, and radiation heat exchange occurs between the inside surface of a wall and the inside surfaces of other walls. Furthermore, solar heat gain through the windows and the radiant heat gain from people, lighting, and equipment affect the temperature of the inside surfaces of walls. It is also assumed that the solar radiation entering through the window is constantly absorbed by the

![Figure 6](image)

**Figure 6.** Parameters affecting the room air temperature.
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Figure 7. Parameters affecting the wall surface temperature.

The temperature of the inside surface of a wall can be calculated from the Equations (6) and (7):

\[
\rho_mC_mV_m \frac{T_m^{p+1} - T_m^p}{\Delta t} = h_mA_m(\theta_{air}^{p+1} - \theta_{air}^p) + k_m \frac{\Delta T_m}{\Delta x_m} + h_{r,m}A_m(MRT_m^{p+1} - T_m^p) + (q_{sol} + q_{r,p} + q_{r,j} + q_{r,e}) \frac{A_m}{A_{all}}
\]

(6)

\[
\rho_rC_rV_r = \rho_rC_r \frac{\Delta T_r}{\Delta x_r}
\]

(7)

where \( \rho_{air} \) is the density of element, \( \text{kg/m}^3 \); \( C_m \) is the specific heat of element \( m \), \( \text{J/kg}^\circ\text{C} \); \( V_m \) is the calculation volume in node of element \( m \), \( \text{m}^3 \); \( h_m \) is the convection heat transfer coefficient for inside surface of element \( m \), \( \text{W/m}^2\text{C} \); \( A_m \) is the area of wall \( m \), \( \text{m}^2 \); \( T_m \) is the temperature of element \( m \), \( \circ\text{C} \); \( k_m \) is the thermal conductivity of element \( m \), \( \text{W/m}^2\circ\text{C} \); \( \Delta x_m \) is the width between nodes, \( \text{m} \); \( h_{r,m} \) is the radiation heat transfer coefficient for inside surface of element \( m \), \( \text{W/m}^2\circ\text{C} \); \( MRT_m \) is the mean radiant temperature of element \( m \), \( \circ\text{C} \); \( q_{sol} \) is the solar heat gain through window, \( \text{W} \); \( q_{r,p} \) is the radiative component of sensible heat gain from people, \( \text{W} \); \( q_{r,j} \) is the radiative component of sensible heat gain from lighting, \( \text{W} \); \( q_{r,e} \) is the radiative component of sensible heat gain from equipment, \( \text{W} \); \( A_{all} \) is the total area of walls, \( \text{m}^2 \).

3. Optimization of ANN model for determination of optimal start and stop times

3.1. Objective of ANN model optimization

It was necessary to optimize the ANN model first for using it to determine the start and stop times of the heating system. The optimization included the minimization of the learning frequency rate and errors to enable the model to quickly adapt to the characteristics of the problem. The application of the ANN to the determination of the start and stop times is different from other general prediction or control applications, as there are many variables to consider.

Furthermore, it is very difficult to optimize the ANN model every time a user uses it. Although the number of nodes in each layer is decided by the input and output variables, model parameters such as the number of hidden nodes and layers, and the learning rate can be freely adjusted by the model designer.

The optimization parameters of the ANN that affect its learning efficiency are the moment, learning rate, number of nodes and bias, and number of hidden layers.

3.2. Selection of input and output variables

First, the parameters that affect the problem must be set as the input variables for ANN learning. Many parameters that influence the heating load affect the determination of the start and stop times of the heating system. These parameters include heating systems, building materials, the internal heat gains, and weather conditions. They can be classified into parameters that do not change during the heating system operation and those that change over a short or long term. Because this study attempted to predict the start and stop times, parameters that change over a short time period were chosen as inputs for the operation of the heating system in winter.

Figure 8 shows the ANN structure. In this study, the input variables comprised not only indoor and outdoor air temperatures but also their variation rates for 1 h for accurately predicting future variations. The output variable was the interval from the start or stop time of the heating system to the time when the target temperature was attained.

- Room air temperature
- Outdoor air temperature
- Changing rate of room air temperature
- Changing rate of outdoor air temperature
- Predicted time to reach the target temperature

3.3. Simulation of thermal analysis using design of experiments

A thermal analysis program was used to generate ANN learning data. Numerous simulations were required to generate learning data for various room conditions. However, the number of simulations required was
impractically large. For example, if there were nine parameters affecting the room air temperature and each parameter was varied at three levels, $3^9 = 19,683$ computer simulations were required, which was infeasible.

However, the same results can be obtained from a small number of simulations by employing the design of experiments (Roy 2001). Representative parameters that affect the room air temperature were chosen as variables and considered in the simulation of various cases with the design of experiments.

The simulation variables that were chosen on the basis of previous research (Yang, Yeo, and Kim 2004; Yang 2010) for improving the performance of the model were: location (weather condition), floor area, target temperature, ceiling height, window area ratio, window shading coefficient, exterior wall structure shown in Table 1, boundary conditions of the room (a) one side facing outdoors and the other sides facing a heating space, (b) two sides facing outdoors and the rest facing a heating space, and (c) four sides facing outdoors), heat capacity of thermal materials, and internal heat gain. The variables and levels chosen for simulating the room air temperature are listed in Table 2. Tables of orthogonal arrays with three levels were constructed for use in the simulations. Twenty-seven simulations were conducted for the experimental conditions of the tables of orthogonal arrays shown in Table 3.

For the generation of the ANN learning data, the room air temperature prediction program was used to

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**Table 1. Structure of walls and slab in simulations.**

| Type         | Section | Material   | Thickness (m) | Thermal conductance (W/m°C) | Thermal capacity (J/m²°C) |
|--------------|---------|------------|---------------|-----------------------------|---------------------------|
| Exterior wall| A       | Mortar     | 0.01          | 0.160                       | 1,450,800                 |
|              |         | Cement brick| 0.09          | 1.320                       | 1,344,000                 |
|              |         | Styrofoam  | 0.19          | 0.036                       | 75,362                    |
|              |         | Cement brick| 0.09          | 1.320                       | 1,344,000                 |
|              |         | Mortar     | 0.01          | 1.160                       | 1,450,800                 |
|              | B       | Plaster board| 0.01          | 0.480                       | 1,209,600                 |
|              |         | Concrete   | 0.10          | 1.396                       | 1,760,000                 |
|              |         | Glass wool | 0.19          | 0.035                       | 67,200                    |
|              |         | Stone      | 0.03          | 2.349                       | 2,164,800                 |
|              | C       | Plaster board| 0.01          | 0.480                       | 1,209,600                 |
|              |         | Glass wool | 0.19          | 0.035                       | 67,200                    |
|              |         | Glass      | 0.006         | 0.780                       | 2,268,000                 |
|              |         | Air        | 0.012         | 0.026                       | 1175                      |
|              |         | Glass      | 0.006         | 0.780                       | 2,268,000                 |
| Window glass | Glass   | Glass      | 0.006         | 0.780                       | 2,268,000                 |
|              | Air     | Air        | 0.012         | 0.026                       | 1175                      |
|              | Glass   | Glass      | 0.06          | 0.0780                      | 2,268,000                 |
|              | Plaster board | Glass wool| 0.01          | 0.480                       | 1,209,600                 |
| Interior wall| Plaster board | Glass wool| 0.10          | 0.035                       | 67,200                    |
|              | Plaster board | Glass    | 0.01          | 0.480                       | 1,209,600                 |
| Slab         | Concrete|           | 0.15          | 1.396                       | 1,760,000                 |
calculate the time required to reach the target temperature after the start and stop of the heating system. The learning data for the 27 spaces were generated by setting the heating system to start between 5:00 a.m. and 7:00 a.m. and to stop between 4:00 p.m. and 6:00 p.m. as in actual buildings. The simulation period was 3 months, from December to February, during which heating systems are usually operated in Korea. The printed outputs in the simulation, which were used as the ANN inputs, were the room air temperature, outdoor air temperature, rate of change of room air temperature, rate of change of outdoor air temperature, and time required to attain the target temperature. The input and output data for the ANN learning was normalized to a value between 0.1 and 0.9 to prevent a specific parameter from dominating the learning.

### Table 2. Variables and levels used in simulations.

| Variables                  | Level |
|----------------------------|-------|
| ① Location                 | Seoul  |
| ② Floor area (m²)          | 100   |
| ③ Target temperature (°C) | 20    |
| ④ Window area ratio        | 0.40  |
| ⑤ Window shading coefficient | 0.40  |
| ⑥ Exterior wall type       | A     |
| ⑦ Adjacent condition       | A     |
| ⑧ Heat capacity of thermal contents (kJ/m²°C) | 9      |
| ⑨ Internal heat gain (W/m²) | 50    |

### Table 3. Tables of orthogonal arrays (L₃² (3⁹)) for design of experiments.

| No. of experiment | No. of column |
|-------------------|---------------|
| 1                 | 1 2 3 4 5 6 7 8 9 | 10 11 12 13 |
| 2                 | 0 0 0 0 0 0 0 0 0 | 0 0 0 0 0 |
| 3                 | 0 0 0 0 0 1 1 1 1 | 1 1 1 1 1 |
| 4                 | 0 1 1 1 0 0 0 0 0 | 0 1 1 1 1 |
| 5                 | 0 1 1 1 1 1 1 1 1 | 1 1 1 1 1 |
| 6                 | 0 1 1 1 1 2 2 2 2 | 2 2 2 2 2 |
| 7                 | 0 2 2 2 0 0 0 0 0 | 0 0 0 0 0 |
| 8                 | 0 2 2 2 2 1 1 1 1 | 1 1 1 1 1 |
| 9                 | 0 2 2 2 2 2 2 2 2 | 2 2 2 2 2 |
| 10                | 1 0 1 2 0 1 2 0 1 | 2 0 1 2 0 |
| 11                | 1 0 1 2 1 2 0 1 2 | 0 1 2 0 1 |
| 12                | 1 0 1 2 2 0 0 0 0 | 0 0 0 0 0 |
| 13                | 1 1 2 0 0 1 1 1 1 | 0 0 0 0 0 |
| 14                | 1 1 2 0 0 1 2 0 1 | 0 0 0 0 0 |
| 15                | 1 1 2 0 2 0 1 1 1 | 0 1 2 1 2 |
| 16                | 1 2 0 1 0 1 2 2 0 | 2 0 0 0 0 |
| 17                | 1 2 0 1 1 2 0 0 0 | 0 0 1 2 0 |
| 18                | 1 2 0 1 0 2 0 0 0 | 0 0 0 0 0 |
| 19                | 2 0 2 1 0 2 1 0 1 | 0 0 0 0 0 |
| 20                | 2 0 2 1 1 2 0 0 0 | 0 0 0 0 0 |
| 21                | 2 0 2 1 1 2 0 2 0 | 2 0 0 0 0 |
| 22                | 2 1 0 2 2 1 0 0 0 | 0 0 0 0 0 |
| 23                | 2 1 0 2 2 1 0 0 0 | 0 0 0 0 0 |
| 24                | 2 1 0 2 2 1 0 0 0 | 0 0 0 0 0 |
| 25                | 2 1 0 2 2 1 0 0 0 | 0 0 0 0 0 |
| 26                | 2 1 0 2 2 1 0 0 0 | 0 0 0 0 0 |
| 27                | 2 1 0 2 2 1 0 0 0 | 0 0 0 0 0 |
The optimal values of the optimization parameters used to determine the optimal start and stop times are shown in Table 4; the values were obtained from the learning results.

For each learning parameter, the optimal values, which minimized the overall errors, were determined by performing learning for each target space (27 cases). It was necessary to assess whether the ANN model developed through this learning process could accurately determine the optimal start and stop times for all the entire target spaces.

The optimized ANN model was trained with the learning data for the input and output for the 27 spaces. The performance of the optimized ANN model was assessed by comparing the output results generated by ANN recall with the output learning data generated by the simulation of room air temperature prediction program. In this study, $R^2$ (the coefficient of determination or multiple correlation coefficient) (Anstett and Kreider 1993) was used as the evaluation index, and it is the most decisive criterion for assessing the output accuracy of ANN recall. The range of $R^2$ was $0 \leq R^2 \leq 1$. When $R^2$ is close to 1.0 (0.0), it implies that the accuracy of the optimized ANN model is high (low). $R^2$ can be calculated from Equation (7):

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (o_i - t_i)^2}{(\bar{t} - t_i)^2} \quad (7)$$

where $o_i$ is the output of the input layer node $i$; $t_i$ is the desired output of the input layer node $i$; $\bar{t}$ is the average of the desired outputs.

Learning was performed 100,000 times by using the optimized ANN model and the recalled data were compared with the output data of the learning process to evaluate the performance of the ANN model in accurately determining the start and stop times for all 27 spaces.

Figure 9 shows that $R^2$, which corresponds to the correlation between the simulation and ANN learning of the start time data, was over 0.990 in most cases (with an average of 0.995). Figure 10 shows that $R^2$, which indicates the correlation between the simulation and ANN learning of the stop time data, was over 0.960 in all cases (with an average of 0.987).

The $R^2$ values show that the optimized ANN model developed in this study could accurately learn the relations between the input and the output for the experimental target spaces and accurately determine the start and stop times of the heating system.

4. Optimization of operation times of heating system

4.1. Daily determination of the optimal start and stop times

Figure 11 shows the basic procedure for the determination of the optimal start and stop times by using the ANN. Since operation data of the concerned building are necessary as prior experience, the preliminary stages consist of collecting operation data. Operation data for the heating system are collected through scheduled or manual control. Once a certain amount of data has been gathered, the start and stop times are determined through the learning of the optimized ANN model, and as more data are gathered, the predicted start and stop times are more accurate.

The detailed procedure for the determination of the start and stop times by using the ANN is shown in Figure 12. When the measurement begins, the outdoor air temperature and room air temperature are measured for each measurement time interval and saved, and after 1 h (in case of the start) or 0.5 h (in case of the stop),

Table 4. Optimized values used to determine the optimal start and stop times.

| Variables         | Start time | Stop time |
|-------------------|------------|-----------|
| Learning rate     | 0.45       | 0.15      |
| Moment            | 0.90       | 0.80      |
| Number of hidden layer | 2          | 1         |
| Nodes of hidden layer | 7          | 9         |
| Bias              | 1.0        | 1.0       |

Figure 9. Correlation between simulation and ANN learning of start time data.
the rates of change of outdoor air temperature and room air temperature are calculated from the temperatures measured at the current time and 1 h or 0.5 h before.

These values are used to calculate the start and stop times for each measurement time interval through ANN recall. Furthermore, the error, which is the difference between the calculated start or stop time and the real start or stop time, is calculated; this error reflects the time from the measurement instant to the start or end of occupancy. If the error is within an acceptable range, the heating system is turned on, and if not, the measurement is continued. Furthermore, if the error drops to within an acceptable range, the equipment is turned on, and if the calculated time exceeds the preset time, the equipment is immediately turned on.

After the heating system is turned on following one of the aforementioned conditions, the outdoor and room air temperatures and their rates of change are saved, and when the room air temperature reaches a predefined temperature, the time taken to reach this temperature from the start or stop time of the heating system is saved. These learning data are provided to the ANN during ANN relearning for obtaining more accurate start and stop times for the following day.

For the daily simulation of the same situations such as those in real buildings, an ANN program and a room air temperature prediction program based on backpropagation learning and the finite difference method were developed, respectively. Additionally, simulations were performed with these programs to optimize the ANN model. It was necessary to evaluate the prediction performance of the optimized ANN model for the start and stop times. Furthermore, it was necessary to determine the amount of initial learning data, acceptable error range, measurement intervals for the input data, and other parameters required for applying the

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**Figure 10.** Correlation between simulation and ANN learning of stop time data.

**Figure 11.** Flowchart for the optimization of the operation times of a heating system.
4.2. Optimization of variables for optimization of operation times

4.2.1. Amount of initial learning data

For the application of the optimized ANN model to the determination of the optimal start and stop times for a real building, operation data of the concerned building are necessary as prior experience. Operation data of a heating system were collected through scheduled or manual control for a specific period. Once a certain amount of operation data were collected, the start and stop times were determined after training the optimized ANN model with the data, and as more data were gathered, the start and stop times could be more accurately determined.

Simulations were performed to obtain the required amount of initial learning data. The occupancy schedule was set from 9:00 a.m. to 6:00 p.m., and the simulation was performed from December 1 to March 10 by using standard weather data for Korea. For the first 20 days, 20 learning data were collected.
with the equipment turned on or off at a certain time, and for the remaining days, the start and stop times were determined after training the optimized ANN model with the collected data. In the determination of the start and stop times by using the optimized ANN model, the model learned the operation data at an early stage, and subsequently, the start and stop times were determined through recall of previously fed unexperienced data.

Figures 13 and 14 show errors in the start and stop times for different amounts of initial data. Clearly, for both start and stop times, the mean error is the smallest when the amount of initial learning data is 20, and it increases with the amount of initial learning data until the data reaches 40. It is inferred that after the acquisition of 20 initial data, the start and stop times could be determined after relearning the data added daily.

4.2.2. Acceptable error range

When the ANN model was used to determine the start and stop times, the heating system was turned on or off as in a real building if the time calculated in a measurement time interval equaled the time remaining until the start or end of occupancy. As depicted in Figure 15, the heating system was turned on at the point where the solid line, representing the time remaining until the beginning of occupancy, meets the dotted line, which represents the start time determined by the ANN model. However, the output of the ANN model may vary, resulting in the times determined being too short 1 day or too long on another day. Furthermore, although the lines in the figure are continuous, in reality, measurement time intervals exist, and therefore, the two lines may not intersect in every interval.

In practice, it is very difficult to always determine the start or stop times from the intersection point of the two lines, and therefore, it is necessary to define a certain range of acceptable error. As shown in Figure 15, the equipment should be turned on when the error is within the acceptable range. The start or stop time determined
in this manner may be slightly early or slightly late, and therefore, the optimal acceptable error range must be determined.

Figure 16 shows results of the start time calculation for different acceptable errors in the range 2–10 min. The mean errors are between 8.0 and 14.6 min for all error levels, and the general trend shows a lower mean error for a lower acceptable error. When the measurement time interval is 3 min, the mean error is 8.0 min.

Figure 17 shows the results of the stop time calculation for different acceptable errors in the range 2–10 min. When the acceptable error is 10 min, the mean errors are the highest, and for the measurement time interval of 4 min, the mean error is the lowest. Therefore, the acceptable error ranges for the determination of the optimal start and stop times are 3 and 4 min, respectively.

4.2.3. Measurement time interval for input data
Because values measured and calculated at certain time intervals were fed to the ANN model as input data and because the start and stop times were calculated for each time interval by using these data, it was necessary to determine the optimal measurement time interval. If the interval is too short, instantaneous local changes in the external variables cause a high error, and if the interval is too long, accuracy is lower. Therefore, it was necessary to determine an appropriate measurement interval.

For the determination of the optimal measurement time interval, simulations were performed by varying the measurement time interval between 1 and 5 min. Figure 18 shows the results of the start time calculation for different measurement time intervals. The mean error in the results ranges between 7.7 and 19.8 min. The mean error increases with the measurement time interval. When the measurement time interval is 1 min, the mean error is the lowest. This implies that the optimal measurement time interval is 1 min. Figure 19 shows the results of the stop time calculation for different measurement time intervals. The mean error of the results is between 11.5 and 18.8 min. When the measurement time interval is 1 min, the mean error is the lowest.

4.3. Analysis of energy-saving effect
As the purpose of optimizing the operation times (through the determination of the optimal start and stop times) of a building heating system by using the ANN was to reduce building energy consumption, an analysis of the energy-saving effect of the optimization was necessary for evaluating the optimized ANN model. The heating energy consumed by the heating system of a building is used for supplying heat at
a specific rate to the room and for energy transport by the supply and return fans, as shown in Figure 6. In this study, all these parameters were considered in the calculation of energy use.

In general, system operators use their discretion to determine the start and stop times, and the heating system is turned on or off through schedule control based on this decision. While heating is turned off when there is no occupancy, it is started before the beginning of occupancy. Therefore, it is very difficult to determine a subjective criterion for the scheduled start time for analyzing the energy-saving effect. Figure 20 shows the average rate of change of energy use for different start times, relative to the energy-increasing effect for a start time of 9:00 a.m. Heating should start prior to occupancy to increase the room air temperature to a predefined level. Therefore, the energy-saving effect varies with the scheduled start time. As shown in Figure 21, a comparison of examples in which the heating system was turned on through time schedule control at 5:00 a.m. with the start of the heating system according to the operation times obtained from the ANN showed that the application of the optimized ANN can reduce energy use by an average of 6.1%.
Figure 22 shows the energy-saving effect, relative to the energy-saving effect for a stop time of 6:00 p.m., for different stop times. The rate of energy saving is in the range 0.9–4.9% (with an average of 2.9%) for the 27 spaces when the stop time used for comparison is 6:00 p.m., which corresponds to the end of occupancy.

5. Conclusions

The purpose of this research was to devise a method for the optimization of the operation times of heating systems in office buildings through the determination of the optimal start and stop times of the heating systems to save energy. Programs for ANN learning and room air temperature prediction based on back-propagation learning and the finite difference method were developed, respectively, and learning data for 27 cases were generated through simulations for the prediction of room air temperature using design of experiments. Furthermore, an ANN model was optimized by training it, and its performance in predicting the optimal start and stop times was evaluated through ANN recall. Finally, variables required for the daily application of the ANN model were optimized and the energy-saving effect of the model was analyzed.

The results of this study can be summarized as follows.
First, the optimized values of the ANN learning parameters for the determination of the optimal start time were obtained as 0.45 for the learning rate, 0.90 for the moment, 2 for the number of hidden layers, 7 for the number of nodes in a hidden layer, and 1.0 for the bias. The optimal values for the determination of the optimal stop time were 0.15 for the learning rate, 0.80 for the moment, 9 for the number of nodes in a hidden layer, 1 for the number of hidden layers, and 1.0 for the bias.

Second, according to the recall results of the optimized model, the multiple correlation coefficient ($R^2$), which represents the correlation between the simulation and ANN learning of the start time data, exceeded 0.990 in most cases (0.995 on average), while the coefficient of determination, representing the correlation between simulation and ANN learning of the stop time data, was above 0.960 in all cases (0.987 on average). This shows that the optimized ANN model developed in this study could accurately learn the relation between input and output for the experimental target space.

Third, for the application of the optimized ANN model to real buildings, the amount of initial learning data and measurement interval for the input data are 20 and 1 min, respectively. The acceptable error ranges for the calculation of the optimal start and stop times are 3 and 4 min, respectively.

Fourth, the energy-saving effect of the use of the optimal start and stop times determined using the optimized ANN for a building heating system was evaluated. Compared to when the heating system was turned on by time schedule control at 5:00 a.m., the application of the ANN was found to reduce energy use by an average of 6.1%. The average rate of energy saving, determined on the basis of the stop time, when the ANN was used was in the range 0.9–4.9% (2.9% on average) for 27 spaces when the stop time used for comparison was 6:00 p.m., which corresponds to the end of occupancy.

In a future research, for the effective application of the ANN, the ANN model and variables suggested in this study will be examined for real building situations and discrepancies between the predicted optimal time and actual time will be analyzed. The developed ANN model can be advantageously embedded in an automatic control system for the optimal control and operation of building heating systems.

Disclosure statement

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