Development of an Artificial Neural Network Model to Predict the Optimal Pre-cooling Time in Office Buildings

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Abstract

This paper presents an application of the artificial neural network (ANN), which is a generic technique for mapping the nonlinear relationships between inputs and outputs without knowing the details of these relationships in building control system. The purpose of this study is to develop an optimized artificial neural network model to determine the optimal pre-cooling time in office buildings. For this, programs for learning of an ANN model based on back-propagation learning and predicting room air temperature based on the finite difference method were developed, and learning data for various building conditions were collected through program simulation for predicting room air temperature using systems of experimental design. Then, the optimized ANN model was presented through learning of ANN and its performance to determine the optimal pre-cooling time was evaluated.

Keywords: artificial neural network; ANN model; cooling system; HVAC; pre-cooling time

1. Introduction

Recently, the necessity of reducing energy consumption has become more important in Korea as in other countries because of a rise in oil prices and a high dependence on foreign energy resources. In Korea, approximately 30% of the total energy is consumed in buildings, and approximately 50% of the building energy is consumed by HVAC systems. Therefore, methods for reducing the energy consumption of HVAC systems in buildings are highly required.

The most effective method is to conserve energy by operating the HVAC equipment during only the occupation times shown in Fig. 1., while providing a comfortable environment to the occupants. However, room air temperature depends on several factors, such as outdoor air temperature, the structure of the building, equipment capacity, etc., so that the room air temperature cannot be kept within the set throttling range immediately after the equipment is turned on. To keep the temperature within the throttling range at the beginning of the occupation time, the equipment must be turned on earlier.

Thus, pre-cooling time is necessary in the summer season to provide comfortable conditions through HVAC equipment operation. However, numerous factors affect pre-cooling time, from outdoor temperature to equipment efficiency, and these factors change constantly, so that it is very difficult to employ the optimal operation conditions considering all related factors. When the pre-cooling time is prolonged and thus the desired room air temperature is reached prior to occupancy, the occupants can obviously be comfortable at the time of occupancy, but the cooling energy is going to be wasted beforehand. Conversely when the pre-cooling time is short because of the late start of the cooling system, the occupants may experience an uncomfortable condition at the time of occupancy. Consequently, the concept of an "optimum pre-cooling time" is needed to determine the optimal start time of HVAC equipment in summer.

The determination of the pre-cooling time is similar to that of the pre-heating time, but the previous study (Levermore, 1992; Park, 1983; Seem, 1989), which considers several factors such as indoor and outdoor air temperature and supplied heat capacity, and mathematical solutions (Tae, 1992) such as recursive equations, is focused on the determination of the pre-heating time.

Here, the control loop of HVAC to determine the pre-cooling time is strictly non-linear, and the characteristics of the equipment vary every year, also the response of the building heat load itself changes. As a result, the coefficients become a non-fixed factor, and the accurate determination of start time becomes impossible.

For optimization of the variables affecting pre-cooling time, these factors must be accurately determined. To do so, data on equipment operation and

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system variation must be collected and analyzed either on-line or off-line for feedback into the control loop. The optimum values obtained by self-investigation of system factor variations and patternization of previous experiences can be used to determine optimum values for other similar patterns.

Therefore, the concept of "learning" based on previous operation data of the building must be introduced to determine the optimum pre-cooling time of systems such as the HVAC equipments. (Nakahara, 1981; Nakahara, 1982; TRANE, 1990)

The artificial neural network (ANN) based on the method of data management by the human brain is a model which searches optimal values by reacting to changes in system properties and by framing prior experience (previous operation experience) into patterns to search for similar patterns. The ANN model which predicts the pre-cooling time must consider all factors that affect the pre-cooling time. Fig.2. shows the basic structure of determination of pre-cooling time in building control systems using the ANN model. ANN model is used to determine the pre-cooling time based on the relation between input and output.

Therefore, the objective of this study is to develop an optimized ANN model which can determine the optimal pre-cooling time of HVAC equipment which is applicable to various building structures, and to evaluate its performance.

2. Theory of Artificial Neural Networks

The science of artificial neural network began in the early 1950s as an attempt to mathematically model the human brain. ANNs, also called "neural networks", "parallel distributed processing", and "connectionist" models, were developed out of the areas of artificial intelligence and cognitive science in their attempts to model the brain and its learning process. ANNs are collections of small individual interconnected processing units with weights associated with each connection. Learning is the first necessary step in inducing intelligence to neural networks. In learning, ANNs are "taught" by presenting sets of patterns to be "learned" and autonomously adjusts the connection weights among processing units according to imposed learning rules and thereby, obtains unique knowledge from the data.

The learned neural network generates accurate outputs for the input data. For inputs that have not been experienced or partially damaged, distorted or mixed with noise, appropriate outputs are generated based on its internal knowledge stored in connection weights. The threshold function is a nonlinear function that decides the output of a particular neuron. Fig.3. shows a popular activation function, called the logistic or sigmoid function. Back-propagation learning (Rumelhart et al., 1986) chosen as the 'training' algorithm in this paper is the name of a supervised training algorithm based on the teacher's (known) data. It is necessary to have both input and output data to train the network. The basic concept of the back-propagation learning is shown in Fig.4., where first, the input patterns of each node are provided at the input layer; then, this signal is converted at each node and transferred to the hidden layer; and finally, the signal generates outputs in the output layer.

\[ f(x) = \frac{1}{1 + e^{(-x)}} \]

Fig.3. Logistic-sigmoid Function and It's Shape

The learning rate of the ANN model is represented by the learning rate parameter. The learning rate parameter determines the rate at which the ANN model adjusts its weights during training. A low learning rate parameter results in slow convergence, while a high learning rate parameter can cause the ANN model to converge too quickly, which can lead to underfitting. The learning rate parameter is chosen based on the desired convergence speed and accuracy of the ANN model.

Fig.4. Schematic Structure of the Back-propagation Learning
The output values are compared to the target values and the connection weights \((w_{ji}, w_{kj})\) are adjusted in the direction which provides less difference between two values using the sigmoid function.

This adjustment is back-propagated from the upper layers to the lower layers, which results in the adjustment of the connection weights in the lower layers. The back-propagation learning algorithm has the following advantages. First, less knowledge, tests, etc. are required to determine input and output relations, whereas even a quadratic system requires a great number of tests and simulations in a mathematical model. Second, deviations from the optimal value or noise signals in on-line learning do not cause significant performance degradation. With mathematical models, using numerous variables can create difficulties in calculation. Third, the ANN models input and output through learning based on prior experience data relations so that no additional input data are needed for the control object. Also, once the given network has finished learning, the response is improved, because the control inputs can be obtained in a short amount of time. In addition, control using the neural network has the unique ability to learn online, thus providing for the implementation of a very flexible control method. Also, it has been used successfully in similar and many applications, such as control (Curtiss, 1992; Kalogirou, 2008; Kreider, 1991; Miller, 1991; Yang, 1999).

3. Thermal Analysis Program for Prediction of Room Air Temperature

3.1 Purpose of a program

Large amount of accurate example data are needed to be input to the ANN model so that it can "learn" and generate accurate solutions. With such data, containing information in a variety of conditions, the neural network model can be optimized to calculate the optimal pre-cooling time. Actual operation data of the building to which the model is being applied are the ideal example data. Here, in the calculation of optimal pre-cooling time, using neural network model as in this study, the model must be optimized using large amounts of data for a variety of conditions. However, the collection of actual operation data of a real building is limited.

Therefore, a computer program, which can provide learning data by simulating various conditions, is needed. In this study, a program that can generate learning data for the ANN so that it can be optimized for various conditions was developed based on the finite difference method (Incropera, 1990).

3.2 Calculation of room air temperature

The room air model for the calculation of air temperature is shown in Fig.5. There is convection heat exchange between room air and inside surface of the wall, and between room air and thermal contents such as furnishings. The room air temperature is determined by the surface temperature of each wall, convection coefficient for walls, the rate of air supply, the rate of infiltration, the internal heat gain from equipment, lighting, people, etc. The thermal equilibrium equation considering convection heat transfer from the surface of the wall and thermal contents, infiltration and indoor heat gain is shown in equation (1). The room air temperature can be determined in the next time step using this equation (1).

\[
\rho_\text{air} C_\text{air} V \frac{T^{p+1}_{\text{air}} - T^p_{\text{air}}}{\Delta t} + h_c A_c (T^p_{\text{wall}} - T^{p+1}_{\text{air}}) + h_f A_f (T^{p+1}_{\text{air}} - T^p_{\text{air}}) + \rho_\text{air} C_\text{air} V_{\text{supply}} (T_{\text{supply}} - T^{p+1}_{\text{air}}) + \rho_\text{air} C_\text{air} V_{\text{infiltration}} (T_{\text{out}} - T^{p+1}_{\text{air}}) + q_c + q_c + q_{e,c} + q_{e,c} (1)
\]

where \(\rho_{\text{air}}\) is the air density; \(C\) is the specific heat; \(V\) is the volume(rate); \(\Delta t\) is the calculation time interval; \(T\) is the temperature; \(h\) is the convection heat transfer coefficient; \(q_c\) is the convection of sensible heat in internal heat gain; superscript \(p\) is the time step number.

Also, there is radiation heat exchange between the inside surface of the wall and inside surface of other walls. Also, there is conduction heat exchange between the inside surface of the wall and the internal wall. The surface temperature of the inside surface wall can be calculated by equation (2).

\[
\rho_m C_m V_m \frac{T^{p+1}_{m} - T^p_{m}}{\Delta t} = h_m A_m (T^{p+1}_{\text{air}} - T^{p+1}_{m}) + k_m A_m \frac{T^{p+1}_{m} - T^{p+1}_{m}}{\Delta x_m} + h_{\text{em}} A_m (MRT^{p+1}_{m} - T^{p+1}_{m}) + q_{r_s} + q_{r_s} + q_{r_s} \frac{A_m}{A_{\text{all}}} (2)
\]

where \(MRT_m\) means radiant temperature of element \(m\); \(q_r\) is the radiation of sensible heat in internal heat gain.

4. The Development of an ANN Model for the Determination of Pre-cooling Time

4.1 Purpose of ANN model optimization

To develop an ANN model to predict the pre-cooling time, first the ANN needs to be optimized.
The optimization means the minimization of errors and learning frequency rate, which implies rapid adaptation to the characteristics of the problem. The application of ANN to determine the pre-cooling time is different from that of other general prediction or control since there are large numbers of variables that must be considered. Also, it is difficult for the user to optimize the neural network model each time it is applied. Even though the number of nodes at the input and output layer is determined by the input and output variables, ANN factors such as the number of hidden layers, nodes in the hidden layer and the learning rate may be freely adjusted by the model designer. Furthermore, how the mentioned factors are constructed plays a decisive role in increasing the learning efficiency and decreasing learning time of the ANN. Unfortunately, only few reports have provided a guideline for making the best selection. After all, these factors must be decided according to the characteristics of the application (Zurada, 1992).

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

4.2 The determination of input and output variables

The ANN model learning begins with setting the factors that affect the problem as input variables. There are many factors of cooling load that affect the determination of the pre-cooling time in buildings including building materials, internal heat gain, HVAC systems and weather conditions. They can be classified into those that do not change during the cooling system operating times, and those that change during the short or long term, etc. Because this study attempts to predict the pre-cooling time, the mentioned factors must be classified as inputs that undergo short-term changes while the HVAC equipment is turned on in the summer season.

Fig. 6 shows the structure of the ANN to predict the pre-cooling time. The input variables in this study consist of not only room air temperature ($i_1$) and outdoor air temperature ($i_2$) but also their variation rates ($i_1$, $i_2$) during 1-hour in order to predict future variations with some accuracy. The output factor is the pre-cooling time ($o_1$) elapsed from the start of the HVAC equipment to the time when the desired temperature was reached.

4.3 Simulation of thermal analysis program using the systems of experimental design

A thermal analysis program is used to simulate ANN learning data to predict the pre-cooling time and numerous simulations are essential to collect the learning data to represent various spaces. For example, if there are 9 factors that affect room air temperature and the factors are each varied three levels, $3^9$ = 19,683 computer simulations are required, which is practically impossible.

However, the same results obtained from numerous simulations that take various factors into consideration to determine the pre-cooling time can be achieved through systems of experimental design (Roy, 2001), which requires only a small number of simulations.

Variables to represent the factors that affect room air temperature were selected and used in the simulation of various cases through the systems of experimental design.

The selected simulation variables were as following: floor area, ceiling height, window area ratio, shading coefficient, internal heat gain, adjacent condition of room, when one side faces outdoors and the remaining sides face the air-conditioned space, (b) when 2 sides face outdoors and the rest face the air-conditioned space, (c) when 4 sides face outdoors, desired temperature, exterior wall structure as shown in Table 1. and heat capacity of thermal contents.

The selected variables and levels for room air temperature simulation are shown in Table 2. In order to use this table, tables of orthogonal arrays of level 3 were constructed. On the basis of the experimental conditions of such tables of orthogonal arrays, the

| Type          | Section | Material   | Thermal conductance (W/m°C) | Thickness (m) | Thermal capacity (J/m°C) |
|---------------|---------|------------|----------------------------|---------------|--------------------------|
| A             | B       | Mortar     | 1.160                      | 0.01          | 1,450,800                |
|               |         | Cement brick | 1.320                    | 0.09          | 1,344,000                |
|               |         | Styrofoam  | 0.036                      | 0.075         | 37,681                   |
|               |         | Cement brick | 1.320                    | 0.09          | 1,344,000                |
|               |         | Mortar     | 1.160                      | 0.01          | 1,450,800                |
| Exterior wall | B       | Plaster board | 0.480                    | 0.01          | 1,209,600                |
|               |         | Concrete   | 1.396                      | 0.10          | 1,760,000                |
|               |         | Glass wool | 0.035                      | 0.075         | 33,600                   |
|               |         | Stone      | 2.349                      | 0.03          | 2,164,800                |
|               |         | Air        | 0.026                      | 0.012         | 1,175                    |
|               |         | Glass      | 0.780                      | 0.006         | 2,268,000                |
|               |         | Plastic    | 0.480                      | 0.01          | 1,209,600                |
| Interior wall | B       | Plastic    | 0.480                      | 0.01          | 1,209,600                |
|               |         | Glass      | 0.035                      | 0.05          | 33,600                   |
|               |         | Plastic    | 0.480                      | 0.02          | 1,209,600                |
| Slab          |         | Concrete   | 1.396                      | 0.15          | 1,760,000                |
Table 2. Variables and Level for Simulation to Predict Room Air Temperature

| Variables                                      | Level |
|------------------------------------------------|-------|
| ① Floor area(m²)                             | 0 50  |
| ② Ceiling height(m)                          | 2.5 2.65 2.80 |
| ③ Window area ratio                          | 0.40 0.65 0.90 |
| ④ Window shading coefficient                | 0.50 0.68 0.85 |
| ⑤ Internal heat gain(W/m²)                   | 50 60 70 |
| ⑥ Adjacent condition                         | a a b c |
| ⑦ Desired temperature(°C)                   | 24 25 26 |
| ⑧ Exterior wall type                         | A B C |
| ⑨ Heat capacity of thermal contents(kJ/m²°C) | 9 12 15 |

conditions of variables were prepared for 27 cases of simulations as shown in Table 3.

To collect the learning data to develop the ANN model for use in determining the pre-cooling time, the room temperature prediction program is used to calculate the time needed to reach the desired temperature after the cooling system starts up. The learning data in 27 spaces could be collected by setting the cooling system to turn on at between 5 am and 7 am as in actual applications. The simulation period included the three months through June to September, during which cooling is usually operated in Korea. The printed outputs of the simulation, which are used as ANN input, are the outdoor air temperature, variation rate of outdoor air temperature, room air temperature, variation rate of room air temperature and time to desired temperature. Here, the desired temperature is the upper limit of the throttling range shown in Fig.1.

Table 3. Simulation Cases Using Tables of Orthogonal Arrays(L₉(3⁴)) of Experiment Design

| No. of experiment | ① Floor area (m²) | ② Ceiling height (m) | ③ Window area ratio | ④ Window shading coefficient | ⑤ Internal heat gain (W/m²) | ⑥ Adjacent condition | ⑦ Desired temp. (°C) | ⑧ Exterior wall type | ⑨ Heat capacity (kJ/m²°C) |
|--------------------|------------------|----------------------|---------------------|-----------------------------|-----------------------------|---------------------|----------------------|-------------------|------------------------|
| 1                  | 50               | 2.50                 | 0.40                | 0.50                        | 50                          | a                   | 24                   | A                 | 9                      |
| 2                  | 50               | 2.50                 | 0.40                | 0.50                        | 60                          | b                   | 25                   | B                 | 12                     |
| 3                  | 50               | 2.50                 | 0.40                | 0.50                        | 70                          | c                   | 26                   | C                 | 15                     |
| 4                  | 50               | 2.65                 | 0.65                | 0.68                        | 50                          | a                   | 24                   | B                 | 12                     |
| 5                  | 50               | 2.65                 | 0.65                | 0.68                        | 60                          | b                   | 25                   | C                 | 15                     |
| 6                  | 50               | 2.65                 | 0.65                | 0.68                        | 70                          | c                   | 26                   | A                 | 9                      |
| 7                  | 50               | 2.80                 | 0.90                | 0.85                        | 50                          | a                   | 24                   | C                 | 15                     |
| 8                  | 50               | 2.80                 | 0.90                | 0.85                        | 60                          | b                   | 25                   | A                 | 9                      |
| 9                  | 50               | 2.80                 | 0.90                | 0.85                        | 70                          | c                   | 26                   | B                 | 12                     |
| 10                 | 100              | 2.50                 | 0.65                | 0.85                        | 50                          | b                   | 26                   | A                 | 12                     |
| 11                 | 100              | 2.50                 | 0.65                | 0.85                        | 60                          | c                   | 24                   | B                 | 15                     |
| 12                 | 100              | 2.50                 | 0.65                | 0.85                        | 70                          | a                   | 25                   | C                 | 9                      |
| 13                 | 100              | 2.65                 | 0.90                | 0.50                        | 50                          | b                   | 26                   | B                 | 15                     |
| 14                 | 100              | 2.65                 | 0.90                | 0.50                        | 60                          | c                   | 24                   | C                 | 9                      |
| 15                 | 100              | 2.65                 | 0.90                | 0.50                        | 70                          | a                   | 25                   | A                 | 12                     |
| 16                 | 100              | 2.80                 | 0.40                | 0.68                        | 50                          | b                   | 26                   | C                 | 9                      |
| 17                 | 100              | 2.80                 | 0.40                | 0.68                        | 60                          | c                   | 24                   | A                 | 12                     |
| 18                 | 100              | 2.80                 | 0.40                | 0.68                        | 70                          | a                   | 25                   | B                 | 15                     |
| 19                 | 250              | 2.50                 | 0.90                | 0.68                        | 50                          | c                   | 25                   | A                 | 15                     |
| 20                 | 250              | 2.50                 | 0.90                | 0.68                        | 60                          | a                   | 26                   | B                 | 9                      |
| 21                 | 250              | 2.50                 | 0.90                | 0.68                        | 70                          | b                   | 24                   | C                 | 12                     |
| 22                 | 250              | 2.65                 | 0.40                | 0.85                        | 50                          | c                   | 25                   | B                 | 9                      |
| 23                 | 250              | 2.65                 | 0.40                | 0.85                        | 60                          | a                   | 26                   | C                 | 12                     |
| 24                 | 250              | 2.65                 | 0.40                | 0.85                        | 70                          | b                   | 24                   | A                 | 15                     |
| 25                 | 250              | 2.80                 | 0.65                | 0.50                        | 50                          | c                   | 25                   | B                 | 12                     |
| 26                 | 250              | 2.80                 | 0.65                | 0.50                        | 60                          | a                   | 26                   | A                 | 15                     |
| 27                 | 250              | 2.80                 | 0.65                | 0.50                        | 70                          | b                   | 24                   | C                 | 9                      |

Table 4. Equations for Normalization of Input and Output

| Variables                                      | Min. | Max. |
|------------------------------------------------|------|------|
| Room air temperature(°C)                       | 25   | 33   |
| Varying rate of room air temperature           | 0    | 1.5  |
| Outdoor air temperature(°C)                    | 14   | 28   |
| Varying rate of outdoor air temperature        | -0.5 | 1.5  |
| Time elapsed to desired temperature(hr)        | 0    | 1.0  |

The input and output data must be normalized for the ANN learning to prevent a specific factor from dominating the learning. In general, normalization gives a value between 0 and 1. However, in this study, the outputs of the simulation program were normalized to generate values between 0.1 and 0.9 by using Table 4.

4.4 Development of ANN Model

The ANN model must be accurately optimized to predict the pre-cooling time in a building with various factors. To optimize the ANN model, first the learning factors such as learning rate, moment, number of hidden layers, number of nodes in each hidden layer, and bias are optimized using the ANN simulation program developed on the basis of back-propagation learning.
The neural network is optimized by learning each learning data of all 27 spaces. A learning factor is systematically varied until the optimal value with minimal error is found. Because of the many factors involved, one factor is optimized while all other factors are fixed. Of the learning data generated through the simulation program, those errors below the value of 0.1 or exceeding 0.9 are removed prior to initiating the neural network learning. The learning is executed 100,000 times using learning data collected by a program for prediction of room air temperature.

The learning results for optimization factors are as follow.

(1) Learning result according to variation in learning rate.

The learning rate plays an important role in the ANN's learning as it determines the magnitude of the error when the connection weights are updated. In order to determine the optimal learning rate, the other factors were fixed as follows: 0.8 moment, 1 hidden layer, 8 nodes in hidden layer and variable bias. ANN learning was performed by varying learning rate of 21 steps (0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.45, 0.50, 0.55, 0.60, 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95, 1.00, 1.50, 2.00). Fig.7. shows that mean error as the learning rate is varied. The mean error for the optimal learning results does not show a significant difference for learning rates over 0.8. Outside of this range, however, the mean error increases and the optimal mean error rate is reached at the 0.90 learning rate.

(2) Learning result according to variation in moment.

The moment is used to increase the learning performance and to shorten the learning time by adding the inertia to equation of connection weights. In order to determine the optimal value of moment which decreases learning time and increases learning efficiency by giving inertia to weight connection, the other variables were fixed as follows: 0.90 learning rate, 1 hidden layer, 8 nodes in hidden layer and variable bias. ANN learning was performed by varying moment of 8 steps (0.60, 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95).

The pattern in mean error according to variation in moment is shown in Fig. 8. The mean error has its minimal value in the moment range 0.70~0.85 and becomes larger as the moment value decreases. Overall, the neural network shows prime efficiency when the moment is 0.8.

(3) Learning result according to variation of hidden layer number.

The number of hidden layers affects the efficiency of the calculation in the ANN's learning and its ability to learn complex input and output relations. Therefore, the appropriate numbers of hidden layers and nodes must be determined considering the learning time and the characteristics of the problem. In order to determine the optimal number of hidden layers, the other factors were fixed as follows: 0.90 learning rate, 0.80 moment, 4 nodes in hidden layer and variable bias.

For the learning data in 27 spaces, the number of hidden layers was changed in four stages from 1 to 4, which are widely used numbers in back-propagation learning. Fig.9. shows how the mean error varies when the number of hidden layers is varied.

The mean error value is relatively small when the hidden layer number is either 1 or 2, and the efficiency is highest when the number is 1.

(4) Learning result according to variation of nodes of hidden layer.

The number of hidden units as a number of hidden layers affects the computational effort required to train the ANN. If there are more hidden units and layers, more calculations must be performed per learning cycle. As the relationships between inputs and outputs become more complex, i.e., nonlinear, more hidden units are needed to learn these complexities. In order to determine the optimal number of nodes in the hidden layer, the other factors were fixed as follows: learning rate 0.90, moment 0.80, number of hidden layer 1 and
variable bias. ANN learning was performed by varying the moment of 9 steps from 4 to 12.

The mean error according to the number of nodes for pre-cooling time is shown in Fig. 10. The optimal efficiency can be achieved with 8~10 nodes. Nine nodes resulted in the smallest mean error.

(5) Learning result according to application of bias

The purpose of biasing is to skew the output from the sigmoid function. There are two methods for adding biases to the ANN: fixed and variable biases.

In order to assess the neural network model according to the presence or absence of bias values, the other factors were fixed as follows: learning rate 0.90, moment 0.80, hidden layer 1 and nodes in hidden layer 9.

For the learning data of 27 spaces, the unused ANN cases were compared with the used cases. Fig. 11. shows the differences in the mean error between the cases with and without bias. The difference between the unused and variable bias was about 5% and the mean error values were generally constant but overall, higher efficiency was achieved with fixed bias.

(6) Optimized ANN model

The optimal values of various learning factors to optimize the neural network model were determined by varying the values of the learning factors and assessing the learning efficiency of the network. The optimized ANN model for the determination of the pre-cooling time from the above results is summarized in Fig. 12.

4.5 Evaluation of the developed ANN model

The optimal values of each learning factor, which could minimize the overall errors, were determined through learning for each target space (27 cases). The ANN model constructed through this learning process must be assessed to determine whether it can determine the optimal pre-cooling time for the entire target space accurately.

The optimized artificial neural network learns using the input and output learning data for the 27 spaces generated by the room temperature prediction program. The performance of ANN was assessed by comparing the output result generated by ANN recall to the output learning data obtained from the simulation of the program.

In order to evaluate whether the optimized neural network model can determine the accurate pre-cooling time for all 27 spaces, learning using the optimized ANN model shown in Fig. 12. was executed 100,000 times and the recalled result was compared with the output learning data in order to assess the performance of the ANN model to determine the pre-cooling time.

Fig. 13. shows that the coefficient of determination ($R^2$) (Anstett, 1993), which is the most decisive criterion for evaluating the accuracy of the ANN model, is over 0.99 in all cases. This means that the optimized ANN model can accurately learn the input and output relations for the experimental target space, and it can be seen that the optimized ANN model accurately determines the pre-cooling time of cooling systems.

5. Conclusions

This paper presents an application of the artificial neural network which is a generic technique for mapping the nonlinear relationships between inputs and outputs without knowing the details of these relationships in a building control system. The purpose of this study is to develop an optimized artificial neural network model to determine the optimal pre-cooling time in office buildings. For this, programs for predicting room air temperature based on the finite difference method and learning of an ANN model based on back-propagation learning were developed, and learning data for 27 cases were collected through program simulation for predicting room air temperature.
using systems of experimental design. Then, an optimized ANN model was developed through the learning of ANN and its performance to determine the optimal pre-cooling time was evaluated through ANN recall.

The results of this study may be summarized as follows.

First, the optimal values of ANN learning factors for the determination of optimal pre-cooling time were shown to be 0.90 for learning rate, 0.80 for moment, 1 for the number of hidden layers, 9 for the number of nodes in hidden layer and fixed value for bias.

Second, the result of performance evaluation using the optimized ANN model showed values over 0.99 for the coefficient of determination ($R^2$). The optimized ANN was shown to be capable of determining the pre-cooling time accurately.

More studies on the effective application of ANN should be conducted in the future. The developed ANN model needs to be applied to real buildings and the discrepancies between the predicted pre-cooling time and the actual time must be evaluated. If the results of such research and previous researches (Yang et al., 2003, Yang et al., 2004) are applied to the EMS (Energy Management System) program of the BAS (Building Automation System), the ANN model will play an important role in building energy saving through the optimal operation of HVAC equipments.

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