Performance evaluation of artificial neural network-based variable control logic for double skin enveloped buildings during the heating season

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Abstract

This study describes integrated logic for an artificial neural network (ANN) to control heating devices on a continuous basis. Two ANN-based control logic systems and two conventional rule-based logic systems were developed to control a heating device and the openings of a double skin enveloped building. The ANN-based logic controls heating devices on a continuous basis according to the indoor temperature. The rule-based logic controls heating systems and openings at envelopes in two-position on/off operation. Control performance for the developed logic was numerically conducted using computer simulations for a small of face space with double skin envelopes during the heating season. Analysis results indicate that the ANN-based temperature control logic resulted in a more stable temperature near the center of the comfortable range with a reduced opening period of the internal envelope. The reduced number of on/off moments of the heating device and the openings in the ANN-based logic were predicted to save energy and prevent system degradation. The use of ANN-based logic would be effective for maintaining a stable thermal environment and for system operation. Rule-based logic can be effectively used to improve building energy efficiency. In this study, two ANN-based logic types were developed for heating devices controlled on a continuous basis and their performance was compared with those of rule-based on/off logic. Thus, in order to cover the limitation of this study, further study is warranted for examining the clear difference achieved by ANN-based vs. rule-based control, when they are applied to control heating output on a continuous basis.

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1. Introduction

The double skin envelope, which consists of internal and external building envelopes, cavity space, openings for ventilation, and shading devices, is a widespread type of building envelope that started being used in recent years. Besides its lightweight structural superiority, one advantage of double skin envelopes is effective control of the indoor environment.

A double skin envelope effectively controls energy flows between indoors and outdoors, and ensures a comfortable indoor visual and thermal environment with improved energy efficiency [1–7]. The control of opening conditions and the cavity space contribute to reduced heating load, cooling load and energy consumption in the thermal environment [8–14]. The application of combined controls affects the indoor thermal condition, which is a critical factor for the occupants' thermal comfort and building energy efficiency [1–3,15–21]. In particular, the thermal buffer zone between internal and external envelopes significantly reduces energy transfer and improves energy efficiency.

In order to examine the influence of thermal buffer zone on energy transfer, control strategies for the use of accumulated energy in a cavity space in winter have been investigated based on two major approaches, rule-based control and optimal control [1]. The rule-based control method employs an intuitively developed simple rule for controlling the openings and the shading device. For example, the openings of the internal surface will be opened when the cavity air temperature is higher than the indoor air temperature. Due to its simplicity, the rule-based control method has been...
widely applied for the thermal control of double skin-enveloped buildings. However, the control strategy determined by the rule-based method was not an optimal solution because it was derived from an intuitive rule set by building managers or occupants. Therefore, better solutions should be created when a prudently developed optimal algorithm is applied.

The effect of an artificial neural network (ANN) has been investigated in terms of its applicability to thermal controls in double skin-enveloped buildings [22–24]. In these studies, the ANN, which is analogous to the human neural structure and learning process, has been successfully applied to non-linear systems or systems with unclear dynamics. Unlike mathematical models such as proportional-integral-derivative (PID) controllers or regression models, the self-tuning process conducted by ANN models results in accurate decisions when unusual disturbances, perturbations and any changes in building background conditions occur.

In other previous studies, ANN-based thermal control methods showed superiority over mathematical strategies in terms of improved thermal conditions with accurate controls and energy efficiency [25–33]. ANN models were developed to calculate the optimal start and stop times for heating systems to provide for energy-efficient system operation and a comfortable thermal environment [25,26].

A similar study was conducted for developing ANN models to predict the optimal end-of-setback moment of air-conditioning systems [27]. The ANN has been successfully applied to operate hydronic heating systems of solar buildings, and to control residential water heating systems and radiant floor heating systems with significant energy savings [28–32].

An ANN model incorporating fuzzy logic was developed to control a radiant heating system [33]. The ANN model was designed to predict the indoor temperature and the fuzzy controller used the predicted value as one of the inputs. The controller markedly reduced overshoots of indoor air temperature and energy consumption compared to proportional-integral (PI) controls.

In particular, various ANN-based optimal control logic methods were developed and tested for various conditions in order to examine the applicability of ANN on thermal controls in double skin-enveloped-buildings [34]. Four ANN models were developed to predict future indoor temperatures for four different opening strategies of openings in envelopes. The control logic compared the predicted indoor temperature and determined the optimal opening strategy for reducing heating energy consumption. The ANN effectively contributed to control the openings and reduce heating energy. The superiority of ANN in terms of optimal control for thermal comfort and energy efficiency has been proved using a performance analysis with a simple rule-based method.

The operation of heating devices with two control options (on/off two-positions) was determined by the control logic. The heating device worked in both predictive and adaptive manners. However, the ANN logic used for the study assumed that heating devices were controlled by on/off-based controls, under which maximum or no heat was supplied to the indoor space.

Although the on/off-based control logic were effectively used for control in a double skin-enveloped building, they are not suitable for controlling heating devices on a continuous basis in modern buildings. Heating devices controlled on a continuous basis supply a certain amount of heat based on specific control algorithms that determine proper thermal output during a certain operation period. In this case, the heating devices produce linear or nonlinear output in order to keep the indoor temperature close to its set point.

Therefore, more advanced ANN control logic should be considered in order to control heating devices on a continuous basis and openings in an integrated manner. Also the control logic should achieve improved thermal control for double skin envelopes, which contain various elements for thermal energy transfer under diverse weather conditions.

In this study, four different types of control logic were developed and applied to control heating devices and openings in the envelopes of a double skin-enveloped building. In order to investigate the effect of ANN-based control logic on heating devices controlled on a continuous basis, the control performance of the four types of logic was examined in terms of thermal elements that are relevant to an indoor thermal environment.

The control performance of the ANN logic was compared with the control performance using rule-based logic, which employed separate control for heating devices and openings in the envelopes, since analysis results in various previous studies are based on conventional rule-based logic that controls heating devices and openings simultaneously.

2. Development of control logics

For integrated control of the heating device and openings in the envelopes of a double-skin-enveloped building, four types of control logic were developed using the different ANN application levels. The developed logic was designed to keep the indoor temperature within a comfortable range based on the integrated control of the heating device and openings.

<table>
<thead>
<tr>
<th>Nomenclature</th>
<th>Description</th>
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<tbody>
<tr>
<td>$U$</td>
<td>output [unitless]</td>
</tr>
<tr>
<td>$U_{\text{NEW}}$</td>
<td>$U$ of the current cycle [unitless]</td>
</tr>
<tr>
<td>$U_{\text{OLD}}$</td>
<td>$U$ of the previous cycle [unitless]</td>
</tr>
<tr>
<td>$U_{\text{TRN}}$</td>
<td>$U$ for the new training dataset [unitless]</td>
</tr>
<tr>
<td>$T_{\text{NEW}}$</td>
<td>air temperature of the current cycle [°C]</td>
</tr>
<tr>
<td>$T_{\text{H}}$</td>
<td>set-point temperature for the heating system [°C]</td>
</tr>
<tr>
<td>$E$</td>
<td>difference between the air temperature and the set-point temperature [°C]</td>
</tr>
<tr>
<td>$E_{\text{OLD}}$</td>
<td>$E$ of the previous cycle [°C]</td>
</tr>
<tr>
<td>$\Delta E$</td>
<td>change in $E$ from the previous cycle [°C]</td>
</tr>
<tr>
<td>$\Delta E_{\text{OLD}}$</td>
<td>$\Delta E$ of the previous cycle [°C]</td>
</tr>
<tr>
<td>$n_i$</td>
<td>number of input neurons</td>
</tr>
<tr>
<td>$n_h$</td>
<td>number of hidden neurons</td>
</tr>
<tr>
<td>$n_o$</td>
<td>number of output neurons</td>
</tr>
<tr>
<td>$n_d$</td>
<td>number of datasets</td>
</tr>
<tr>
<td>$\text{TEMP}_{\text{ON}}$</td>
<td>indoor air temperature change from the preceding cycle</td>
</tr>
<tr>
<td>$\text{TEMP}_{\text{CAV}}$</td>
<td>cavity air temperature</td>
</tr>
<tr>
<td>$\text{TEMP}_{\text{OLD}}$</td>
<td>outdoor air temperature</td>
</tr>
<tr>
<td>$\text{TEMP}_{\text{PR}}$</td>
<td>predicted air temperature</td>
</tr>
<tr>
<td>$\text{INPUT}$</td>
<td>input value for the input neuron</td>
</tr>
<tr>
<td>$\text{INPUT}_{\text{ACT}}$</td>
<td>actual value of each thermal factor</td>
</tr>
<tr>
<td>$\text{INPUT}_{\text{MAX}}$</td>
<td>maximum value of each thermal factor</td>
</tr>
<tr>
<td>$\text{INPUT}_{\text{MIN}}$</td>
<td>minimum value of each thermal factor</td>
</tr>
</tbody>
</table>

$\text{INPUT}_{\text{MIN}}$, $\text{INPUT}_{\text{MAX}}$, $\text{INPUT}_{\text{ACT}}$, $\Delta T$, $\Delta T_{\text{CAV}}$, $\Delta T_{\text{OLD}}$, $\Delta T_{\text{NEW}}$, $e$, $f$, $\alpha$, $\beta$, $\gamma$, $\delta$, $\lambda$, $\mu$, $\nu$, $\xi$, $\psi$, $\phi$, $\chi$, $\rho$, $\sigma$, $\tau$, $\omega$, $\Omega$, $\Theta$, $\Lambda$, $\Xi$, $\Sigma$, $\Upsilon$, $\Phi$, $\Psi$, $\Omega$, $\Delta$, $\nabla$, $\epsilon$, $\zeta$, $\eta$, $\theta$, $\iota$, $\kappa$, $\lambda$, $\mu$, $\nu$, $\xi$, $\omicron$, $\pi$, $\rho$, $\sigma$, $\tau$, $\upomega$, $\alpha$, $\beta$, $\gamma$, $\delta$, $\epsilon$, $\zeta$, $\eta$, $\theta$, $\iota$, $\kappa$, $\lambda$, $\mu$, $\nu$, $\xi$, $\omicron$, $\pi$, $\rho$, $\sigma$, $\tau$, $\upomega$.
Fig. 1 presents the basic composition of the four types of logic. ANN-based methods and rule-based methods were designed to respectively control heating devices and the openings of double skin envelopes. Logic type I employed two ANN models for both components. Logic type II used an ANN model for the heating devices and a rule for the openings. Logic type III employed a rule for heating devices and an ANN for the openings. Logic type IV, which represents the widespread conventional approach, employed specific rules for controlling the heating device and the openings.

Fig. 2 shows the algorithm of logic I. The algorithm was composed of two major processes. The first process was to operate the heating device and the second process was to operate openings in the envelopes. Two ANN models were applied to determine the thermal output of the heating device and the opening conditions for the envelope.

The first ANN model was applied to predict the operating ratio (U) of the heating device between 0 and 1. This logic could be applied to a heating device that provides heat on a continuous basis according to the change in the indoor temperature.

The neural network toolbox in MATLAB was used to develop the ANN model. The structure of the model is presented in Fig. 3. It was composed of an input layer, a hidden layer, and an output layer. Two neurons (E and ΔE) comprised the input layer. E is the difference between the indoor air temperature and the set-point temperature (°C), and ΔE is the changing amount of E from the previous cycle (°C). The number of neurons in the hidden layer (5) was determined using Equation (1) [35,36].

One output neuron was applied for U, which denotes the operating ratio of the heating device. Identical to the ANN model for the surface openings, the Tangent Sigmoid and pure linear methods were applied as the transfer functions for the hidden and output neurons, respectively.

\[ n_h = 2 \times n_i + 1 \]  
\[ N_d = (N_h - (N_i + N_o)/2)^2 \]

The training method for the ANN model is summarized in Table 1. The Levenberg–Marquardt algorithm, a 0.75 learning rate, a 0.90 moment, and a 0.00 K2 goal with a 1000-time epoch were employed for training based on the findings in the previous study [37]. In addition, 25 datasets were prepared for training, using Equation (2) [37]. To manage the training datasets, the sliding-window data management technique was applied. The ANN model process for operating the variable heating device is summarized below.

(a) Find \( U_{\text{TRN}} \) using \( U_{\text{OLD}} \), \( T_{\text{NEW}} \), and \( T_{\text{H}} \).

For this, Equation (3) is used.

\[ U_{\text{TRN}} = U_{\text{OLD}} + U_{\text{OLD}} \times (T_{\text{H}} - T_{\text{NEW}}) \]  

For example, when the set-point temperature is 21.5 °C, the current temperature is 21.3 °C, and the operating ratio of the heating device during the previous cycle is 0.35. Then \( U_{\text{TRN}} \) is determined to be 0.42. This means that the operating ratio should have been 0.42 in the previous cycle.

(b) Find \( E_{\text{OLD}} \) and \( \Delta E_{\text{OLD}} \).

For example, if the indoor temperature of the previous cycle and of the two cycles before it are 20 °C and 19.9 °C, respectively, then \( E_{\text{OLD}} \) is -1.5 °C (20 – 21.5 °C) and \( \Delta E_{\text{OLD}} \) is 0.1 °C ((20 – 21.5 °C) – (19.9 – 21.5 °C)).

(c) \( E_{\text{OLD}}, \Delta E_{\text{OLD}}, \) and \( U_{\text{TRN}} \) are used as new training datasets.

Using the sliding-window data management technique, the new set is added to the training datasets, replacing the oldest.

(d) Train the ANN model with the new training datasets.

(e) Using the trained ANN model, \( U_{\text{NEW}} \) for the current cycle is calculated.

Then the heating device will work following the calculated \( U_{\text{NEW}} \). The second ANN model was applied to control the opening conditions of envelopes. In every control cycle, the ANN model was
trained to be adapted to the new environment. Then, this trained ANN model could predict the future indoor temperature (TEMPIN) for the different opening strategies, which are summarized in Table 2.

Using the predicted values, the optimal opening strategy was determined. The optimal opening strategy for the internal and external envelopes was to create the warmest indoor temperature by the next control cycle. For example, if the indoor temperature predicted by the ANN model for the four opening strategies are +1.0 °C (case 1), −1.3 °C (case 2), +1.3 °C (case 3), and −1.5 °C (case 4), then the optimal opening strategy is case 3, where the openings of the internal envelope are open and those of the external envelope are closed. Finally, the optimal opening strategy for the openings was implemented before the ending of the algorithm.

The structure of the ANN model for determining the opening condition is shown in Fig. 4. One input layer, four hidden layers, and one output layer comprise the ANN model. The optimal number of hidden layers was derived in a previous study [1].

Diverse neurons were employed in the input layer. Each of the neurons represented factors relevant to the heat transfer process between the indoor and outdoor environments. The opening conditions of the internal and external envelopes and the indoor temperature (TEMPIN), cavity temperature (TEMPCAV), and outdoor air temperatures (TEMPOUT) determine the amount of convective heat transfer.

In addition, the amount of conductive heat transfer is affected by the indoor, cavity, and outdoor air temperatures. Along with these five factors, ∆TEMPIN, which is the indoor air temperature change from the preceding cycle, was considered in the input layer. This factor indicated the current change in the status of the indoor temperature condition.

The amount of solar radiation was not included in the input layer due to its inconsistent correlation with the indoor temperature in a previous study [39]. The coefficient of determination (R²) was significant when the sun consistently existed in the daytime. However, the coefficients for overcast sky conditions, partly cloudy sky conditions and nighttime were insignificant as determinants of the indoor temperature. Due to this inconsistency, the amount of solar radiation was excluded as an input variable.

The actual values of the input variables were 0 (closed) and 1 (opened) for the opening conditions of the envelope, −10 to 40 °C for TEMPIN, −10 to 10 °C for ∆TEMPIN, −20 to 40 °C for TEMPCAV, and −20 to 80 °C for TEMPOUT. These actual values were normalized using Equation (4) to have a number between 0 and 1 before entering the input neurons [39].

\[
\text{INPUT} = \left( \frac{\text{INPUT}_{\text{ACT}} - \text{INPUT}_{\text{MIN}}}{\text{INPUT}_{\text{MAX}} - \text{INPUT}_{\text{MIN}}} \right)
\]

The number of neurons in the hidden layer was optimally determined to be 10 based on the previous optimization process [39]. The optimal number was applied to produce the most accurate output of the model. The number of output neurons was determined to be 1, the future indoor temperature by the next control cycle (TEMPIN).

The Tangent Sigmoid and pure linear methods were applied as the transfer functions for the hidden and output neurons, respectively. The Sigmoid transfer function is a commonly applied method in back-propagation networks based on its accuracy. In particular, the Tangent Sigmoid function is known to be a good solution for multilayer networks [40].

Table 3 summarizes the parameters for the training process. The same number of hidden layers, a 0.75 learning rate, and a 0.30 moment for the optimal training were determined in the previous study [39]. The training goal of the model was 0.01 K², with a 1000-time epoch. In addition, the number of training datasets was 85 based on Equation (2) [39]. The training data are updated using the sliding-window data management technique. Thus, the oldest set was removed when the new dataset was obtained [1,37,38].

Fig. 5 shows the algorithm of logic type II. This logic employed the same process employed by logic I for determining the operating conditions of the heating device. A specific rule was employed for operating the openings of the envelopes. When the cavity air temperature (TEMPCAV) was higher than both the upper limit of the heating range and the indoor temperature (TEMPIN), the openings of the internal envelope were opened to bring the heated cavity air into the indoor space. Otherwise, the openings were closed. Based on these two rules, the heating device and the openings changed their operating conditions to maintain a comfortable indoor temperature.

The algorithm of logic III is presented in Fig. 6. A specific rule was employed for determining the operating condition of the heating device, which had a two-position operating mode (on/off). The current operating condition of the heating device and the current indoor temperature (TEMPIN) worked as determinants for deciding the next operating condition of the heating device. For example, if the heating device is working and the indoor temperature is over the upper limit of the heating range (e.g., 23 °C), the heating system will be turned off. For operating the openings of the surface, the ANN model, which is identical to that of logic I, was applied.

The algorithm of logic IV is shown in Fig. 7. This logic employed two specific rules for operating the heating device and opening the

**Table 2**

<table>
<thead>
<tr>
<th>Number of opening strategy</th>
<th>Internal openings</th>
<th>External openings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>Closed</td>
<td>Closed</td>
</tr>
<tr>
<td>Case 2</td>
<td>Closed</td>
<td>Opened</td>
</tr>
<tr>
<td>Case 3</td>
<td>Opened</td>
<td>Closed</td>
</tr>
<tr>
<td>Case 4</td>
<td>Opened</td>
<td>Opened</td>
</tr>
</tbody>
</table>

**Table 1**

<table>
<thead>
<tr>
<th>Training parameters for ANN model for heating device.</th>
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</thead>
<tbody>
<tr>
<td>Training methods [37]</td>
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<tr>
<td></td>
</tr>
<tr>
<td>Training data management technique [1,37,38]</td>
</tr>
</tbody>
</table>
envelopes. Rules were identical to those of logics II and III, respectively.

3. Numerical performance tests

Performance tests were conducted using the four control logics in order to examine the influence of logic on indoor thermal environment and energy consumption. The performances of the four types of control logic were numerically tested for a one-story space with double skin envelopes.

A detailed description of the space is shown in Fig. 8. The dimension of the space was 4.2 m wide, 4.5 m deep and 3.05 m high. The main façade covered with double skin envelopes was facing south. The depth of the cavity space was 0.9 m. Openings were installed at the top and bottom of the internal and external envelopes for the air inlet and outlet. Each opening was 0.5 m wide and 0.3 m high.

The $R$-values (thermal resistance) of the envelope components were 5.00, 2.78, and 2.44 m² K/W for the roof, wall, and floor, respectively. The $R$-values of glazing used for the internal and external envelope were 0.18 m² K/W and 0.77 m² K/W, respectively.

Two seated occupants conducting light of face tasks, two computers with printers, and 5 W/m² of lighting fixtures were considered as internal loads. Ventilation and infiltration rate was assumed to be 0.7 ACH (air change rate per hour), and no shading devices and external obstructions around the building were considered.

A radiative heating system with a 7172 kJ/h heat supply capacity was installed for space heating. Four types of control logic described in section 2 were employed to control the heating system to maintain the indoor temperature within the specified range (20–23 °C) or set-point temperature (21.5 °C).

The test space was assumed to be located in Seoul, South Korea (latitude: 37.56° N, longitude: 126.98° E). The performance tests were conducted for conditions of the space with double skin envelopes from January 1 to March 31, which represents the heating season. The TMY2 weather data for the designated location was used for the numerical test.

TRNSYS (Transient Systems Simulation) and MATLAB (Matrix Laboratory) were incorporated for the performance tests. Fig. 9 shows the process of incorporating TRNSYS and MATLAB. The TRNSYS software is a package for energy simulation that can simulate diverse building systems and performances [42]. In this study, it was used for (1) modeling the test building components and related features (e.g., double-skin facade, a heating device, initial thermal conditions, internal load, import of weather data, and ventilation and infiltration rate) and (2) calculating the indoor temperature (TEMPₜₙ) as a result of the heating device operation and other related components.

MATLAB is a numerical computing and programming software package [40]. In this study, it was used for (1) developing control logic and ANN models, (2) predicting the indoor temperature (TEMPₚₗ) using the developed ANN models and data from TRNSYS, and (3) determining the operation of the heating device and the opening conditions of openings at envelopes based on the control logic.

The decisions regarding the heating device and the opening conditions were fed into TRNSYS to actually operate the heating device and openings. Adopting these decisions, TRNSYS produced a new indoor temperature condition, and this new indoor temperature was transferred to MATLAB. This incorporative process was repeated at every control cycle, which was defined to be 1 min in this study.

The validity of the incorporative simulation method was proven in previous studies [1,11]. The variation in indoor temperature collected from an actual building was statistically compared with the predicted indoor temperature variation using an ANN model. The analysis results showed a significant relationship between the

![Fig. 4. A structure of artificial neural network model for openings.](image-url)
collected and predicted values, with a significantly smaller root mean square of errors (RMS) at 0.0259 K than the designated goal of the ANN models (0.1 K RMS). The accuracy of the simulation method, therefore, was validated for testing the performances of diverse control logic.

4. Test results and analysis

4.1. Thermal performance

In order to determine the influence of the four types of control logic, the variation in the indices that can be used to evaluate indoor thermal environment were selected in this study. The indices were indoor temperature, cavity temperature, outdoor temperature, comfortable period for indoor thermal conditions, and opening period of openings in the internal envelope. Figs. 10–13 show the temperature profiles, heating operation, and conditions of openings in the internal envelope which were controlled by the four types of logic from March 11 to 20.

The influence of logic I is shown in Fig. 10. The outdoor air temperature fluctuated between 0.40 °C and 19.99 °C. The variation pattern in the cavity temperature was very similar to that of the outdoor temperature during the time period because the cavity air temperature was directly affected by the outdoor air temperature. In addition, this logic employed ANN models to control the heating device on a continuous basis and the opening conditions of the internal envelope. Using the decisions from the ANN model, the heating device worked continuously according to a control setting from 0.00 to 1.00. Thus, the indoor temperature was maintained near the center of the comfortable range (21.5 °C).

The openings of the internal envelope were closed for most of the sampled period because the developed ANN-based algorithm was determined to close the internal envelope to keep the indoor temperature within the comfortable range. The cavity air, which was warmer than the indoor air, was not brought into the indoor space. Thus, the indoor temperature deviated less from the upper limit of the comfortable range (23 °C). The highest cavity air temperature was higher than that set by logic II because the heated cavity air stayed in the cavity space. The highest cavity temperatures set by the logic were 27.93 °C.

Fig. 11 shows the effect of logic II on the indoor thermal environment. As the same ANN model is applied for the heating device, the operation of the heating device shows a pattern that is similar to that of logic I. Therefore, the profile of the indoor air temperature was also similar to that of logic I. In logic II, the heating device worked with different ratios between 0.09 and 0.29 based on the output from the ANN model (U).

Although the indoor air temperature was maintained within a comfortable range, the temperature rose up out of the comfortable range in certain instances. This phenomenon has also commonly occurred with logic I, due to the relatively warmer outdoor and cavity air. During these periods, the output (U) for the heating device was close to 0. To operate the openings of the internal envelope, a specific rule was applied. Thus, the internal openings were opened when the cavity air temperature was higher than the
indoor air temperature on the third day of the sampled period. The indoor temperature of the highest moment was 27.02 °C.

Fig. 12 presents the results of control logic III, which used the specific rule for the heating device and the ANN model for the openings of the internal envelope. When a specific rule was applied for operating the heating device, the indoor air temperature was normally kept within the comfortable range (20–23 °C) when the heating device was operated.

However, as opposed to logic II, the openings of the internal envelope were closed for the entire sampled period because of the decisions from the developed ANN-based algorithm for maintaining a better indoor temperature within the comfortable range. This is a similar result to that of logic I.

Fig. 13 shows the results of logic IV, which employed rules for controlling both the heating device and openings of the internal envelope. The profiles of indoor temperature and heating system operation showed a similar pattern with that of logic III. In addition, the internal envelope was opened more frequently compared with the cases controlled by the other three logics.

The influence of the four types of developed logic on indices for indoor thermal environment during the whole test period is summarized in Table 4. The average indoor temperature was closer to the center of the comfortable range (21.5 °C) when the ANN model was applied for operating the heating device (logic I and II). This was because the amount of heat supply was increased by the specific rule which was employed in the algorithm. The average indoor temperatures were 20.45 °C, 20.62 °C, 20.09 °C, and 20.09 °C, for logic I, II, III and IV, respectively.

For the same reason, when the ANN-based control logic for heating devices was used, the period in which the temperature was lower than the comfort range was shorter compared to the case in which rule-based logic was employed. When rule-based control for a heating device was used, the period in which the temperature was lower than the comfort range was 2.9% of the total test period. The period was reduced to 0.88% and 0.38% when the ANN-based logic was used for control.

The period where indoor temperature was higher than the comfort range was increased by the ANN-based control logic for heating devices. The amount of increase reached 8.16% from 4.18%. However, the output (U) of the heating device controlled by the ANN model was close to 0 even when the indoor temperature was maintained over the comfortable range. This means that an uncomfortably high temperature was caused by the thermal inertia of the indoor space rather than by the operation of the heating device in the current control cycle.

The opening period of the internal envelope was longer when rule-based logic was used for the control of openings at envelopes. Logic types II and IV opened the openings at the internal envelope for 197 and 934 min, respectively. The opening period of openings in the internal envelope was shorter when ANN-based logic was used to control the openings. The opening period controlled by logic I and III was 111 and 0 min.

This phenomenon was due to the fact that the ANN model determined that the closing of the openings in the internal envelope is beneficial to maintain more comfortable indoor temperature conditions. For example, the ANN-based logic for the control of openings (logic I) reduced the opening period by 86 min compared
to the rule-based logic (logic II). This results in an increase in the comfortable temperature period of as much as 3.57%.

In summary, the ANN-based temperature control logic for double skin enveloped-buildings provided more stable conditions within the comfortable range with a reduced opening period of the openings in the internal envelope.

4.2. Energy efficiency

The influence of four types of control logic on energy consumption was examined in this study. The amounts of heat supplied from the heating device are shown in Fig. 14. Two ANN-based logic approaches supplied more heat to the indoor space. Logic I and logic II supplied 1598.31 kWh and 1629.85 kWh, respectively. The amount of heat supply was decreased by two rule-based control logics. Logic III and IV supplied 1536.89 kWh and 1537.28 kWh heat, respectively. Compared to logic I, the decreases were 3.84% and 3.82%, respectively.

The two ANN-based logic types for control of the heating device (logic I and II) supplied more heat to the indoor space. Logic I and II supplied 1598.31 kWh and 1629.85 kWh, respectively. The amount of heat supply was decreased by two rule-based control logics (logic III and IV). Logics III and IV supplied 1536.89 kWh and 1537.28 kWh, respectively. Compared to logic I, the amount of heat supply was decreased by 3.84% and 3.82%, respectively.

This increase in the ANN-based logic was due to the fact that the rule employed in logic types I and II guaranteed a non-working period for the device with two control options (on/off), while the ANN-based logic types kept the heating device working continuously in much of the period, even though the output (U) from the ANN model was close to 0.

Due to the application of the rule, the number of on/off changing moments of the heating device for the whole test period was much larger with logic types III and IV (7.523 and 7.519 times, respectively) while those with logic types I and II were 182 and 52 times, respectively. This result occurred identically for the work-time period from 9:00 a.m. to 18:00 p.m. during the test period. The numbers of on/off changing moments were 8, 3, 109, and 105, respectively, for control logic types I, II, III and IV.

This was because the rule-based control logic types guaranteed the turning off of the heating device when the indoor air temperature rose over the comfortable range while the ANN-based logics changed the output (U) to keep the temperature close to the center of the comfortable range. Due to the reduced number of on/off moments, the ANN-based heating device control logics are expected to potentially compensate increased energy consumption and improve energy efficiency in the long run.

In summary, rule-based control logic for heating devices required less heat supplied to the indoor space. Indoor temperature controlled by the rule-based logic was lower compared to the case when the ANN model was applied to control heating devices. The reduced number of on/off moments by the ANN-based control logic reduced heat consumption and prevented system degradation and failure.

5. Conclusions and future research

This study suggests integrated control logic types for optimum control for heating devices on a continuous basis and opening options for the openings in the envelopes of double skin-enveloped buildings. Four different control logics were developed using a combination of conventional rule-based control and purely ANN-based control. The influence of control logic on the indoor thermal environment was examined under various conditions in winter. A summary of findings is as follows.

(1) The two ANN-based logic types for the heating devices (logic I and II) provided more heat to the indoor space and kept the indoor temperature higher compared with the rule-based logic for heating devices. The average indoor temperature
Fig. 11. Temperature profiles, heating operation, and opening conditions of the internal openings (logic II, March/11–March/20).

Fig. 12. Temperature profiles, heating operation, and opening conditions of the internal openings (logic III, March/11–March/20).

Fig. 13. Temperature profiles, heating operation, and opening conditions of the internal openings (logic IV, March/11–March/20).
controlled by the two ANN-based logic types was higher and closer to the center (21.5 °C) of the comfortable range.

(2) The rule-based logic for the control of heating devices (logic III and IV) successfully kept the indoor temperature within the comfortable range (20–23 °C) for much of the test period, except for certain periods when the warm air in the cavity space was brought into the indoor space. During these periods, the indoor temperature rose over the comfortable range even though heating devices were not operated.

(3) The ANN-based opening control logic types (logics I and III) effectively reduced the opening periods of openings in the internal envelope, since the ANN models determined that the closing of the openings in the internal envelopes is beneficial to maintain more comfortable temperature conditions. Accordingly, logic types I and III supplied longer comfortable periods, respectively, compared to logic II and IV, which used the rule to control opening options in the envelopes.

(4) Two rule-based logic types for the control of heating devices (logic III and IV) supplied less heat to the indoor space since the employed rule guaranteed a non-working period for the heating device. This resulted in a lower indoor temperature compared with the result might differ from that with ANN-based logic. Due to those limitations, further study should be conducted in order to examine the clear difference achieved by ANN-based vs. rule-based control, when they are applied to control heating output on a continuous basis according to the change in indoor temperature. Further study that covers the limitations is being currently prepared by the authors of this study.

In addition, further research needs to be conducted for actual buildings, since computer simulations were used as a primary analysis tool. By analyzing the results from the actual buildings for diverse conditions during various seasons, sound bases for the application of ANN-based optimal control logic will be obtained. Also, the logic to control a cooling device and openings should be developed for seasons when cooling is necessary. In this case, air conditioning systems will be more efficient over conventional rule-based logic: (i) more stable temperature conditions near the center of the comfortable range, (ii) warmer indoor temperature conditions based on the increased heat supply, and (iii) less possibility of system degradation or failure due to the reduced number of on/off moments of the heating device.

On the other hand, the rule-based control logic showed two strengths: (1) it was simple to develop, and (2) it slightly increased the comfortable period with less heating energy consumed. Therefore, it will be beneficial to use ANN-based logic for a stable thermal environment and system operation. Rule-based logic can be effectively used to improve building energy efficiency.

In this study, two ANN-based logic types were developed and applied for heating devices controlled on a continuous basis in order to examine the influence of logic on indoor thermal environment. The analysis results were compared with those of two rule-based logic types which control the heating devices on an on/off-based control. Although the rule-based control was independently applied for heating devices and openings at envelopes, the result might differ from that with ANN-based logic.

The result of this study implies that ANN-based temperature control logic for double skin enveloped-buildings can provide three advantages over conventional rule-based logic: (i) more stable temperature conditions near the center of the comfortable range, (ii) warmer indoor temperature conditions based on the increased heat supply, and (iii) less possibility of system degradation or failure due to the reduced number of on/off moments of the heating device.

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### References
