Application of control logic for optimum indoor thermal environment in buildings with double skin envelope systems

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ABSTRACT

This study proposes an effective thermal control method for thermally comfortable and energy-efficient environments in buildings with double skin envelopes. Four rule-based control logics and an artificial neural network (ANN)-based control logic were developed for the integrated control of openings and cooling systems in summer. Using numerical computer simulations, the performance of the proposed control logics was comparatively tested in terms of thermal performance and energy efficiency.

Analysis results imply that the more detailed rules of thermal control logic were effective to maintain the indoor temperature conditions within comfortable ranges. The ANN-based predictive and adaptive control logic presented its potential as an advanced temperature control method with an increased temperature comfort period, decreased standard deviation of temperature from the center of the comfortable range, and decreased number and ratio of overshoots and undershoots out of the comfort range. The additional rules embedded for control logic or ANN applications yielded a more comfortable temperature environment in an integrated manner according to the properly designed operations of envelope openings and the cooling system. However, logics with additional rules and ANN models consumed more energy for space cooling. Therefore, the rule-based controls with advanced logics or an ANN model are required in case occupant comfort is a primary factor to be satisfied. In other cases, the simple rule-based logic is effectively applied.

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1. Introduction

Curtain wall structures covered with glazing materials have been effectively applied to high-rise commercial buildings due to the advantages of reducing the structural loads of buildings. Despite these advantages, buildings with curtain wall structures present weak insulation levels of envelopes and difficulty controlling the penetration of solar irradiance into the indoor space from outdoors. Accordingly, the weakness of envelopes in terms of the thermal environment and energy consumption results in increasing heating and cooling loads due to the inappropriate heat transfer between outdoor and indoor environments.

In order to reduce such inappropriate heat transfer, double skin envelopes have been applied to buildings with curtain wall structures. The double skin envelope, which is composed of internal and external envelopes, openings for air inlets and outlets in each envelope, a cavity between the internal and external envelopes, and shading devices, helps reduce heating and cooling loads and energy consumption [1–7].

The cavity space between internal and external envelopes primarily contributes to reducing the load and energy consumption, since the space functions as a thermal buffer zone for controlling the amount of energy transfer between indoor and outdoor environments. Appropriate controls of air inlets and outlets installed at the internal and external envelopes also work effectively to reduce thermal loads and energy consumption.

The double skin envelope can be strengthened when the relevant components for controlling the amount of energy transfer between the indoor and outdoor environments are properly installed and operated. For example, the opening conditions of internal and external envelopes effectively determine the amount of convective heat transfer (i.e., ventilation) between indoor and outdoor environments.

The indoor temperature condition, which is one of the most important factors in determining the thermal comfort of
occupants, is closely related to the opening conditions at the envelopes. For proper operation of the openings, diverse rule-based strategies have been studied and applied [8–10]. These control strategies employ simple rules for controlling the openings of the envelopes. For example, the openings at the external envelope are always closed and those at the internal envelope are open when the cavity temperature is over 28 °C in winter. Due to their simplicity, rule-based control strategies have been most widely applied to the control algorithms. A specific rule for operating the openings controls the amount of heat transfer by conduction, ventilation, and solar radiation.

Although diverse strategies employing specific rules have been introduced for the control of the thermal environment in buildings with double skin envelopes, they have two major limitations. Primarily, the criterion and algorithm for deciding the opening conditions of the air inlets and outlets of the envelopes is determined intuitively by building managers or occupants. The cavity temperature or the amount of solar radiation are used as determinants, but other thermal factors such as indoor and outdoor temperature are not employed in the control logic.

Secondly, the existing rule-based control methods cannot control the openings and the thermal control systems in an integrated manner. The air inlets and outlets of the envelopes are controlled independently without any interactions with the heating or cooling systems. The respective criterion for controlling openings and thermal control systems is cavity temperature and indoor temperature.

Therefore, new methods that can synthetically consider the related thermal factors and system components need to be developed to optimize thermal controls and energy efficiency. This study proposes an effective thermal control method for greater thermal and energy efficient environments in buildings with double skin envelopes. Several rule-based control logics and artificial neural network (ANN)-based control logics were developed for the control of openings and cooling systems in summer. The performance of the proposed control logics was compared in terms of thermal performance and energy efficiency.

The developed control logics commonly considered the cavity temperature and indoor temperature in the control algorithm to determine the operation of the air inlets and outlets as well as the cooling system. The ANN-based logic additionally used outdoor temperature and the opening conditions of the envelope in the algorithm. Considering relevant components in the algorithm, the logic was expected to provide a more comfortable thermal environment.

The proposed logics were designed to operate the openings of envelopes and the cooling system in an integrated manner, in which the operating conditions of the cooling system affect the decision for the opening conditions of the envelopes. Due to the contribution of the integrated method, energy could be consumed more efficiently for thermal control in buildings.

2. Development of control logics for indoor temperature

The temperature control logics considered in this study were developed in two categories. The first one was a rule-based control logic, which employs specific rules to control the openings and the cooling system. Four different logics were organized with diverse rules. The second one was an ANN-based logic that uses the predictive and adaptive controls of the opening and cooling systems.

2.1. Rule-based control logics

The algorithms and descriptions of the different assumptions and features of each algorithm used for the rule-based control logics are shown in Figs. 1–4 and Table 1. The developed rule-based control logics synthetically employed the indoor and cavity temperatures as well as the operating conditions of the cooling system in the algorithm in order to determine the operation of the air inlets, outlets, and cooling system.

The first rule-based logic, which is shown in Fig. 1, employs the current operating condition (ON or OFF) of a cooling system, indoor temperature, and cavity temperature as determinants. Based on these determinants, the operation of the cooling system and the openings of internal and external envelopes are determined. For
example, when the cooling system is working (ON), the algorithm checks the indoor temperature condition. If the indoor temperature is under the lower limit of the cooling range (e.g., 23 °C), the cooling system stops working (OFF).

The opening conditions of the internal and external envelopes are determined by the cavity temperature. When the cavity temperature is over the lower limit of the cooling range, the openings of the internal envelope are closed because the induction of air in the cavity can cause the indoor temperature to rise. This process is explained in Table 1. On the other hand, if the cavity temperature is under the lower limit of the cooling range, the internal envelope is opened to bring the cool air in the cavity into the indoor space. In both cases, the openings of the external envelope are opened to remove potentially heated air in the cavity. A similar process occurs when the cooling system is not working (OFF).

The second rule-based logic shown in Fig. 2 is identical to the first logic except that it compares the cavity temperature and the marginal degree for inducting cavity air in order to decide the opening conditions of the internal envelope. That is, the second rule-based logic closes the internal envelope if the cavity temperature is lower than the marginal degree as described in Table 1. For example, if the marginal degree for inducing air is 20 °C and the current cavity temperature is 19 °C, then the internal envelope will be closed. This decision prevents the induction of cold cavity air into the indoor space and maintains indoor temperature within the comfortable range. Employing this logic, the indoor air is expected to be controlled effectively within the comfortable range.

The third rule-based logic shown in Fig. 3 is identical to the first logic except that the new assumption relevant to indoor temperature is added for operating openings of the internal envelope. When the indoor temperature exceeds the upper limit (e.g., 26 °C) of the cooling range or falls below the lower limit (e.g., 23 °C), the openings of the internal envelope are closed regardless of the cavity temperature.

This process assumes that the indoor condition, which is over 26 °C or under 23 °C means that the cavity air is, respectively, too hot or cold to bring in. For example, when the cooling system is
Table 1
Assumptions and features of the four rule-based control logics.

<table>
<thead>
<tr>
<th>Rule-based controls</th>
<th>TEMPIN Assumptions</th>
<th>Features</th>
<th>TEMPCAV Assumptions</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>–</td>
<td>–</td>
<td>• When TEMPCAV is above 23 °C, it is too hot to bring to indoor.</td>
<td>• Above 23 °C: close the openings of internal surfaces.</td>
</tr>
<tr>
<td>(2)</td>
<td>–</td>
<td>–</td>
<td>• Same as (1)</td>
<td>• Under 23 °C: open the openings of both surfaces.</td>
</tr>
<tr>
<td>(3)</td>
<td>• When TEMPIN is above 26 °C, it is too hot to bring the outdoor and cavity air to indoor. • When TEMPIN is under 23 °C, it is too cold to bring the outdoor and cavity air to indoor.</td>
<td>• Over 26 °C or under 23 °C: close the openings of internal surfaces.</td>
<td>• Same as (1)</td>
<td></td>
</tr>
<tr>
<td>(4)</td>
<td>• Same as (3)</td>
<td>• Same as (3)</td>
<td>• Same as (1)</td>
<td>• Under 20 °C: close the openings of internal surfaces.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• When COOLINGin is same with COOLINGCav, keep the current opening condition for preventing continuous changing the opening conditions.</td>
<td>• Same as (1)</td>
</tr>
</tbody>
</table>

not working and the indoor temperature and cavity temperature are 20 °C and 15 °C, respectively, then the openings of the internal envelope are opened if the first rule-based logic is applied. Indoor temperature will decrease and become less comfortable due to the cold cavity air. However, if the third rule-based logic is applied, the openings of the internal envelope will be closed in order not to take cold cavity air into the indoor space. Thus, the indoor temperature will be maintained better within the comfortable range.

The fourth rule-based logic shown in Fig. 4 is the same as the third logic except that it compares the previous and current operations of the cooling system in order not to frequently change the opening conditions of the internal envelope. For example, if the cooling system is not working and the indoor temperature is close to the lower limit of the cooling range (e.g., 23 °C), and it moves up and down repeatedly according to the opening conditions of the internal envelope, then the opening conditions will change frequently at every control cycle. Thus, the new determinant is added, and it compares the current and previous operating conditions of the cooling system. When the previous and current operating conditions are identical, the opening condition of the internal envelope remains in the same position.

2.2. ANN-based control logic

Artificial neural network (ANN) is another possible method for controlling the opening conditions of the double skin envelopes of buildings. ANN is analogous to the human neural structure and its learning process, and has been increasingly applied to the field of building thermal controls due to its predictability and adaptability [11].

The ANN models applied in the control logic predict future indoor thermal conditions based on the current and past conditions. The predicted values can be applied to the optimal control of the relevant components for the advanced thermal environment. In addition, the ANN model iteratively trains itself to adapt to the new environments. Its superiority over mathematical methods such as proportional-integral-derivative (PID) controllers or regression models has been proven in terms of thermal comfort and energy efficiency [11–15].

In this study, the ANN-based control logic was designed to maintain indoor temperature stably within comfortable ranges by way of the integrated control for the openings of building envelopes and a cooling system. Fig. 5 describes a conceptual flow of the incorporative process between the control logic and ANN model for controlling indoor temperature in double skin envelope buildings.

The incorporative process consists of three major steps. The first step is to collect data that are relevant to the indoor thermal condition, such as current indoor temperature, previous indoor temperature, outdoor temperature, cavity temperature, and opening conditions of the internal and external envelopes. The collected data are fed into the ANN models as input values.

The second step is to apply ANN models to predict future indoor temperature conditions. Four individual future indoor temperatures are predicted for the four opening strategies of the internal and external envelopes, which are summarized in Table 2. For this prediction, four independent ANN models were developed to predict the amount of undershoot or overshoot of indoor air temperature (TEMPin). The amount of undershoot or overshoot means the maximum drop or rise, since the current working mode of the cooling system is changed. For example, undershoot of the air temperature is the maximum drop of air temperature after the currently working cooling system is stopped.

The third step is to determine the optimal opening strategy and to operate openings and the cooling system. Based on the

Table 2
Opening conditions of openings at internal and external envelope [16].

<table>
<thead>
<tr>
<th>Cases</th>
<th>Openings of internal envelope</th>
<th>Openings of external envelope</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Closed</td>
<td>Closed</td>
</tr>
<tr>
<td>2</td>
<td>Closed</td>
<td>Opened</td>
</tr>
<tr>
<td>3</td>
<td>Opened</td>
<td>Closed</td>
</tr>
<tr>
<td>4</td>
<td>Opened</td>
<td>Opened</td>
</tr>
</tbody>
</table>
comparison of the four predicted values, the control logic determines the optimal opening strategy for the openings, implements the decided strategy, and operates the cooling system.

The control logic presented in Fig. 6 employs the incorporative process as explained. Four independent ANN models predict the indoor temperature under the four opening strategies for the internal and external envelopes. Based on the current operating condition, the optimal opening strategy is decided. After comparing the operating range of the cooling system and the summation of current (TEMPIN) and predicted (TEMPPR) temperatures, the new operating condition of the cooling system is determined. The new operation of the cooling system and the optimal opening strategy are then performed.

For example, when a cooling system is working, the optimal opening strategy for internal and external envelopes is to provide the greatest undershoot of indoor temperature. If the predicted undershoots by the ANN models are $-0.7^\circ\text{C}$ (case 1), $-1.8^\circ\text{C}$ (case 2), $+0.2^\circ\text{C}$ (case 3), and $+2.1^\circ\text{C}$ (case 4), then the optimal strategy is case 2, in which the openings of internal and external envelopes are closed and opened, respectively. Employing case 2, the cooling system can be turned off earlier than in other cases. A similar process is followed when the cooling system is not working. Since the openings and the cooling system can be controlled in this predictive manner, indoor air temperature is expected to be conditioned within comfortable ranges with enhanced energy efficiency.

Four ANN models were developed to predict the overshoot or undershoot of the indoor air temperature for the four opening strategies of the double skin envelopes summarized in Table 2. Three advantages can be provided by applying the ANN models in the control logic. First, the relevant factors, whose relationships to the indoor temperature are statistically proven, can be selected as input variables for operating openings at the envelopes and the cooling system. Second, the openings and the cooling system can be operated in a predictive and adaptive method. Third, the indoor temperature conditions are controlled in an integrated manner considering openings and the cooling system simultaneously.

Fig. 7 shows structures of the developed ANN model. The ANN model is composed of one input layer, six hidden layers, and one output layer. Table 3 summarizes the detailed conditions for the variables. Heat transfer in buildings comprises convection by ventilation and infiltration, and conduction through envelope, solar radiation, and internal loads such as occupants, lighting fixtures, and equipment. The amount of heat transfer by convection and conduction in buildings with double skin envelopes is associated with the indoor, outdoor, and cavity temperatures, and the opening conditions of the internal and external envelopes. In addition, the variation of direct and diffused irradiance from the sun and sky under certain sky conditions affects the total amount of solar irradiance to the envelope.

The input variables were selected based on the relevant components of the heat transfer process. Indoor air temperature (TEMPIN), the amount of air temperature change from the previous control cycle ($\Delta$TEMPIN) – which was assigned as 1 min in this study.
according to a suggestion from a previous study [16], outdoor temperature (TEMP\textsubscript{OUT}), cavity temperature (TEMP\textsubscript{CAV}), and opening conditions of the internal and external envelopes functioned as input variables.

However, solar radiation was not considered as an input variable, since statistical tests conducted in a previous study revealed that the correlation between solar irradiance and indoor temperature was not always significant [17]. In the study, the coefficient of determination ($R^2$) of prediction models that imply the relationship between solar irradiance and indoor temperature was 0.0204, 0.0060, and 0.0853 for overcast sky, partly cloudy sky, and clear sky, respectively.

Since the model needed to work properly for the variance of the sky conditions, solar irradiance was excluded from the input variables. In addition, internal loads were not considered as input variables, since the amount normally changes according to the

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**Fig. 6.** Logic for controlling cooling system and openings of the double skin envelope.

**Fig. 7.** Structure of the developed ANN model.
occupants' behaviors. Using Eq. (1), the actual values of input variables in Table 3 were normalized to be between 0 and 1.

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

(1)

The optimization process was conducted in a previous study to decide the number of hidden layers, the number of neurons in the hidden layers, and training methods [17]. The number of hidden layers and the number of neurons in each hidden layer were determined as 6 and 13, respectively, to produce the most accurate outputs as summarized in Table 3. The tangent sigmoid and pure linear transfer functions were used in the hidden and output neurons, respectively.

For the training process, 0.60 and 0.40 were assigned as the learning rate and moment, respectively. The Levenberg–Marquardt algorithm was applied for the training algorithm, and the sliding window method was employed to manage the 91 training data sets. Thus, when the new training data set was newly acquired, the new set replaced the oldest set in order to reflect the latest conditions in the ANN model. As the iterative training process was conducted for the ANN models, the control logic could adapt itself for changes or disturbances around double skin enveloped-buildings to produce more accurate outcomes.

3. Performance tests of the developed logic

The numerical performance tests of the developed rule-based and ANN-based temperature control logics were conducted using the Transient Systems Simulation (TRNSYS) and the Matrix Laboratory (MATLAB) in an incorporate manner. TRNSYS is an energy simulation software program that can model and simulate building systems and performance [20]. MATLAB is a numerical computing and programing software, and its neural network toolbox was employed to develop the ANN model [21].

In this study, TRNSYS software was used to (1) model the test building and relevant features (e.g., import of weather data, double skin envelopes, cooling system, initial temperature and humidity conditions, internal load, and ventilation and infiltration rates), and (2) calculate the indoor temperature (TEMP_{IN}) based on the operation of openings of double skin envelopes and the cooling system.

MATLAB was used to (1) develop the ANN model and temperature control logic, (2) determine the operation of opening conditions of the envelopes based on the ANN models, and (3) determine operation of the cooling system based on temperature control logic. The decisions for the operation of openings and the cooling system were fed into TRNSYS. Adopting the new operation of openings and the cooling system, a new indoor temperature was calculated in TRNSYS, and the new result was transferred to MATLAB. The incorporative process between TRNSYS and MATLAB repeated at every control cycle, which was assigned as 1 min in this study.

Fig. 8 shows the modeling procedure of a targeted building using MATLAB and TRNSYS. Type 155 was used to connect MATLAB-based control logics to the TRNSYS environment. The validity of the applied simulation method was proved using the comparison between indoor temperatures predicted by an ANN model and measured indoor temperatures in an actual building [12,16,17,22,23]. In those studies, the statistical significance for the relationship between the predicted and measured temperatures was proved with a smaller root mean square of errors (0.0259 K) than the designated goal of the ANN models (0.1 K). Thus, the simulation method could be used for further performance tests.

In this study, performance tests of the developed rule-based logics and ANN-based logic were conducted in the one-story double skin envelope building in summer in terms of indoor temperature conditions and cooling energy efficiency. Fig. 9 shows a detailed layout of the tested building, which was assumed to be located in Seoul, South Korea (Latitude 37.56°, Longitude 126.98° East).

The dimensions of the building were 4.5 m deep, 4.2 m wide, and 3.05 m high. The main façade where double skin envelopes were installed was facing south. The cavity space was surrounded by internal and external envelopes, and the cavity depth was 0.9 m. At the top and bottom of each envelope, a series of openings for air inlets and outlets were installed with dimensions of 0.5 m wide and 0.3 m high. The induced air through the inlets was assumed to pass naturally through the cavity space and go out through the outlets according to the opening strategies. The thermal resistances (R-values) of envelope components were 2.78 m² K/W for walls, 5.00 m² K/W for the roof, and 2.44 m² K/W for the floor. The R-values of external and internal envelopes were 0.18 m² K/W and 0.77 m² K/W, respectively.

The internally generated heat gain was assumed to comprise the two seated light-work occupants, 5 W/m² of lighting fixtures, and two computers with printers. The infiltration rate was fixed as 0.7 air change per hour (ACH). A convective cooling system with heat removal capacity of 6,315 kJ/hr was installed for cooling with an operating range of 23–26°C. External obstructions around the building were not considered in this study.

The performance tests for the four rule-based control logics and ANN-based control logic were conducted for the cooling season from June to September of 2012. The TMY2 weather data assigned for the building location in computer simulation programs were used for performance tests.

4. Results

The performances of the developed control logics were analyzed in terms of temperature conditions such as temperature profiles, average indoor temperature, comfortable period, standard deviation from the center of the comfortable range, features of overshoot and undershoot of temperature, and the amount of heat removed by the cooling system.
4.1. Temperature conditions by control logics

The performances of the rule-based and ANN-based logics were compared in order to examine the influence of control logics on the variation of indoor temperature. Figs. 10–14 respectively show the indoor temperature profile according to the operation of the cooling system and openings of the envelopes for two days in July among the four months of test period used in this study.

The indoor temperature conditions, the operation of the cooling system and envelope openings by rule-based and ANN-based logics showed slightly different patterns. The first rule-based control logic maintained indoor temperature within the comfortable range when the cavity temperature was above the lower limit of the cooling range (23°C), as shown in Fig. 10. During such a period, the internal envelope was entirely closed in order not to bring warm air into the indoor space. Instead, the cooling system worked properly to lower the indoor temperature even though there had been overshoots and undershoots that deviated from the operating range at every on/off moment in the cooling system.

However, when the cavity temperature was significantly lower than 23°C, the indoor temperature was also below the lower limit of the comfortable range. The cold air brought to the indoor space through openings of the internal envelope caused this negative phenomenon. Therefore, the average temperature and the comfortable period generated by this logic were the lowest (23.57°C and 69.94%), as shown in Figs. 15 and 16, respectively. Consequently, this logic produced the largest standard deviation from the center of the comfort range (2.15°C) as 1.95°C, as shown in Fig. 17. The results imply the instability of the temperature conditions.

The second rule-based control logic, which considered the marginal degree (20°C) of the cavity air to be induced indoors, showed a similar temperature profile when the cavity air temperature was over the lower limit of the cooling range (23°C), as shown in Fig. 11. However, the difference occurred when the cavity temperature was under the marginal temperature for inducing air (20°C). When the cavity air temperature was under 20°C, the internal envelope was closed in order to avoid bringing cold air into the indoor space. Therefore, the indoor temperature was kept higher than that by the first rule-based control logic even though it was not warmed enough within the comfortable range. The average temperature and the comfortable period were increased to 24.08°C and 75.91%, as shown in Figs. 15 and 16, respectively.
The standard deviation was decreased to 1.32 °C, as shown in Fig. 17.

The third rule-base control logic, which employed an additional rule for operating the openings of the internal envelope, also kept similar temperature conditions for a period when the cavity air temperature was maintained at the lower limit of the cooling range (23 °C), as shown in Fig. 12. On the other hand, due to the new rule, the internal envelope was closed when both indoor and cavity
temperatures were under 23 °C. Consequently, the internal envelope was iteratively opened and closed in a short cycle, which probably causes failure in the opening system. As shown in Figs. 15–17, the average temperature, comfortable period, and standard deviation were similar to those generated by the third rule-based control logic (24.05 °C, 73.56%, and 1.31 °C, respectively).

The fourth rule-based control logic, which compared the previous and current operations of the cooling system in order to not frequently change the opening conditions of the internal envelope
showed more comfortable temperature conditions than the other rule-based logics, as shown in Fig. 13. Several negative impacts of the other rule-based control logics (such as cold indoor temperature or frequently changing opening conditions) no longer occurred. Accordingly, the average temperature and comfortable periods were all increased to 24.74 °C and 90.26% as shown in Figs. 15 and 16, respectively, while the standard deviation was decreased to 1.02 °C as shown in Fig. 17. However, the overshoots and undershoots that deviated from the operating range still existed at every on/off moment of the cooling system.

The ANN-based control logic maintained indoor temperature most comfortably, as shown in Fig. 14. Similar to the fourth rule-based control, the indoor temperature stably existed within the comfortable range, and the openings of the internal envelope did not repeat their operations. In particular, from 8:03 a.m. to 12:16 p.m. on July 12th, the openings of the internal envelope were kept open to bring the relatively cool cavity air in indoors. This operation was determined by the ANN model, which compared the opening strategies and decided to open the internal envelope as an optimal method. The average temperature was 24.70 °C, as shown in Fig. 15, and the comfortable period was increased slightly to 90.76%, as shown in Fig. 16. The standard deviation of temperature was similar to that generated by the fourth rule-based control logic, as shown in Fig. 17.

Analysis of the temperature profile, average temperature, comfortable period, and standard deviation of temperature revealed that the fourth rule-based and ANN-based control logics showed superiority based on the proper operations of openings and the cooling system. The comfortable periods increased while the standard deviations from the center of the comfortable range decreased.

4.2. Overshoots and undershoots of temperature conditions by control logics

The analysis of the features of overshoots and undershoots was conducted in terms of number and ratio. The results are summarized in Table 4. The first rule-based control logic produced the fewest overshoots and undershoots, since the internal envelope was opened even when the cavity air temperature was too cold to bring in. The indoor temperature was kept cold under the comfortable range, thus, the cooling system was less needed. As the additional rules were included in the control logic from the second to fourth rule-based logics, the number of on and off cycles of the cooling system was increased, resulting in an increased number of overshoots and undershoots out of the comfortable range. The ANN-based logic produced slightly more overshoots and undershoots compared to the second and third rule-based control logics, because the cold cavity air was not brought into the indoor space.

The percentage of overshoots and undershoots out of the comfortable range was 100% for all the rule-based controls. This means that the indoor temperature was outside of the comfortable range at every moment when the operating mode of the cooling system changed. However, the percentage was reduced to 85.33% for overshoots and 84.51% for undershoots by the ANN-based control logic. The cooling system by the ANN-based control logic was turned on and off earlier than by the rule-based control logics based on the predictive determination. Accordingly, the indoor temperature was not out of the comfortable range. This reduction supports the potential that the ANN-based logic can maintain the indoor temperature more stably within the comfortable range, and has a thread of connection with the reduced standard deviation of indoor temperature from the center of the comfortable range.

4.3. Amount of heat removal by control logics

The amounts of heat removal per floor area from the indoor space were analyzed to examine the effect of diverse control logics on building energy efficiency in summer. Fig. 18 shows the amount of heat removed by the control logics. The first rule-based control logic removed the least amount of heat, which was 33.98 KW/h/m² for the test period. This was because the cold air in the cavity was brought indoors even though it was not warm enough for supply. Therefore, the comfortable period generated by this logic was significantly lower than those generated by other logics.

The second and third rule-based control logics removed similar amounts of heat (as much as 36.87 KW/h/m² and 36.76 KW/h/m², respectively), which represented increases of 8.51% and 8.19% compared to the first control logic. Their average temperatures and comfortable periods were also similar, as explained in the previous section.

On the contrary, the fourth rule-based control logic conducted a significantly increased cooling operation culminating in heat removal of as much as 48.89 KW/h/m². The increasing amount of heat removal reached 43.90% compared to the first rule-based logic, due to the additional rule by which the previous and current operations of the cooling system were compared to prevent frequent changes of the opening conditions of the internal envelope. Accordingly, cool air in the cavity space was less induced into the indoor space.

When the ANN-based control logic was applied, the amount of heat removal from the indoor space was 47.58 KW/h/m², which was 1.4 times that of the first rule-based control logic and 0.97
Table 4
Total number and ratio of overshoots and undershoots by diverse control strategies.

<table>
<thead>
<tr>
<th>Month</th>
<th>First rule-based control</th>
<th>Second rule-based control</th>
<th>Third rule-based control</th>
<th>Fourth rule-based control</th>
<th>ANN-based control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jun.</td>
<td>880/880</td>
<td>1230/1230</td>
<td>1177/1177</td>
<td>1481/1481</td>
<td>1177/1313</td>
</tr>
<tr>
<td>Jul.</td>
<td>1394/1394</td>
<td>1410/1410</td>
<td>1351/1351</td>
<td>1586/1586</td>
<td>1476/1444</td>
</tr>
<tr>
<td>Aug.</td>
<td>1321/1321</td>
<td>1333/1333</td>
<td>542/542</td>
<td>978/978</td>
<td>606/906</td>
</tr>
<tr>
<td>Sep.</td>
<td>311/311</td>
<td>567/567</td>
<td>4502/4502</td>
<td>5696/5696</td>
<td>4885/4838</td>
</tr>
<tr>
<td>Total</td>
<td>3906/3906</td>
<td>4540/4540</td>
<td>100/100</td>
<td>100/100</td>
<td>75.21/83.90</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Ratio of overshoot and undershoot out of the comfortable range (%)</th>
<th>Jun.</th>
<th>100/100</th>
<th>100/100</th>
<th>100/100</th>
<th>50.42/46.62</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Jul.</td>
<td>100/100</td>
<td>100/100</td>
<td>100/100</td>
<td>98.46/72.26</td>
</tr>
<tr>
<td></td>
<td>Aug.</td>
<td>100/100</td>
<td>100/100</td>
<td>100/100</td>
<td>90.77/88.81</td>
</tr>
<tr>
<td></td>
<td>Sep.</td>
<td>100/100</td>
<td>100/100</td>
<td>100/100</td>
<td>66.74/59.78</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>100/100</td>
<td>100/100</td>
<td>100/100</td>
<td>85.33/84.51</td>
</tr>
</tbody>
</table>

5. Conclusions

This study proposes an effective thermal control method for a thermally comfortable and energy-efficient environment in buildings with double skin envelopes. Four rule-based control logics and the ANN-based control logic were developed for the control of openings and cooling systems in summer. The performance of the proposed control logics was tested using computer simulations, and comparatively analyzed in terms of thermal performance and energy efficiency. The findings of this study are summarized as follows.

(1) The control logic employing the simplest rule conditioned indoor temperature least comfortably. Its comfortable period was the shortest, and the standard deviation for the indoor temperature from the center of the comfortable range was the greatest. As the advanced rules for supporting the thermal comfort were added, temperature conditions were improved with increased comfortable periods.

(2) The ANN-based control logic showed its potential as an advanced temperature control method. The ANN model predetermined the operation of the openings of the envelope and of the cooling system, culminating in an increased temperature comfort period and decreased standard deviation of the indoor temperature from the center of the comfortable range.

(3) For identical opening conditions the ANN-based logic significantly reduced the number and ratio of overshoots and undershoots out of the comfortable range, due to the predictive and adaptive features of the ANN models. Based on the reduced overshoots and undershoots, the ANN-based logic proved that it could maintain the indoor temperature more stably with a more comfortable thermal environment.

(4) The simplest rule-based control logic removed the least heat from the indoor space, as the cold cavity air was brought into the indoor space for a longer time. This result means that this logic can save cooling energy. On the contrary, since the rules were complicated, more heat was removed from the indoor space. A similar phenomenon occurred when the ANN-based control logic was applied.

In conclusion, additional rules or ANN applications could create a more comfortable temperature environment based on the appropriate operations of envelope openings and the cooling system in an integrated manner. However, it might consume more energy for space cooling. This implies that two perspectives in terms of thermal comfort and energy efficiency can be involved in selecting the proper temperature control logic. If occupant comfort is the primary factor to be satisfied, then the complicated rules or ANN model will be required. Otherwise, the simple rule-based logic will be applied usefully.

Further study is required to investigate the economic impact of the rule-based logic and ANN-based logic, such as energy cost and systems installation cost. Analysis of the overall economic impact will more concretely demonstrate the potentials of the proposed control logic. In addition, the developed logics need to be applied to actual buildings under diverse weather conditions.

In addition, new consideration is required in the logic for the nighttime ventilation during summer season. During the nighttime when the outdoor air is significantly colder than the comfort range and the building is vacant, cold outdoor air is useful to cool down the building mass. The proposed logic in this study will be modified to employ different ways of openings at envelopes for the occupants and vacant periods.

Air temperature and overall thermal quality such as enthalpy also needs to be considered as a control target for advanced thermal comfort. For this, the logics will be modified in future study and their performance will be comparatively tested with that of control logics proposed in this study.

Finally, the proposed logics are needed to be applied to the test chamber and actual buildings under diverse weather conditions. In particular, the proposed logics are needed to be applied to the various types of double skin envelope systems such as a shaft box type or multi-story double skin façade in which the cavity air temperature is vertically different. When the vertical temperature difference causes the malfunction of the control logics, the sensors have to be installed in multi-locations in the cavity space, for example, a temperature sensor on each floor. Based on the performance analysis in real buildings, the concrete validity of the proposed logics will be intensified.
Acknowledgment

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References