Determining optimum control of double skin envelope for indoor thermal environment based on artificial neural network

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ABSTRACT

This study aims to develop an artificial neural network (ANN)-based temperature control method to keep energy efficient indoor thermal environment in buildings with double skin envelope systems. Control logic that effectively controls the opening conditions of air inlets and outlets of the double skin envelope as well as the operation of the cooling system was developed employing the ANN model. To determine the optimal structure and learning methods for the ANN model, a parametrical optimization process was conducted in terms of the number of hidden layers, the number of neurons in the hidden layers, learning rate, and moment; this process was followed by performance tests of various optimized models. Analysis of the performance tests proved predictability and adaptability of the developed ANN model for diverse background conditions in terms of stable root mean square (RMS) and mean square error (MSE) values. The developed ANN model showed strong potential as a temperature control method for indoor thermal environment of buildings with double skin envelope systems.

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1. Introduction

Double skin envelope (DSE) systems have been applied as an alternative to mitigate energy consumption in buildings constructed with a traditional curtain wall structure that has single envelope. DSE systems showed strong potential for maintaining a favorable indoor thermal environment with improved energy efficiencies. In order to find the optimal configurations of the DSE and to test their effectiveness, diverse studies have been conducted [1–7]. In particular, recent studies have been focused on developing advanced control strategies for the air inlet and outlet located on both internal and external building envelopes. It was shown that appropriate control operations of the openings that allow air flow through cavities in the DSE effectively controlled the indoor thermal environment and reduced energy consumption for heating and cooling [8,9].

Control of the opening is achieved using a variety of control methods to save energy usage in buildings. The rule-based control strategy is the mostly widespread control method for operating inlets and outlets of the envelope due to the simplicity of the design algorithm and the fact that it is easily applied to buildings [10]. However, limitations still exist for these methods. Because the rules are intuitively developed in many cases, the existing rule-based methods may not be an optimal solution for operating openings to control the thermal environment to both meet the needs of the occupants and improve building energy efficiency. In addition, the current rule-based control methods are not able to be adaptively applied in buildings exposed to various weather conditions.

In order to improve these limitations, this study aims to develop an artificial neural network (ANN)-based temperature control method that optimally controls the air inlets and outlets of internal and external building envelopes, as well as cooling systems applied to buildings. To achieve the research objective, this study consists of four steps. First, temperature control logic was developed for the proper operation of air inlets and outlets at the internal and external skins, as well as the cooling system used for buildings. Secondly, an ANN model was developed and employed in the temperature control logic for predictive and adaptive controls. Thirdly, the structure and the learning methods of the developed ANN model were optimized using an optimizing process. Finally, the results from optimized prediction models were validated against analysis results from field measurements under diverse weather conditions and building orientations.
The application of the optimized ANN model to the proposed temperature control logic effectively contributes to the control of indoor temperature in a predictive and adaptive way. This results in maintaining energy-efficient indoor space and overcoming the existing limitations of control for buildings with double skin envelopes.

2. Development of control logic for indoor air temperature

A control logic, which is based on the rule-based control method, was developed for optimal control of cooling systems and cavity openings in order to maintain a favorable indoor air temperature required for thermal comfort in the most energy-efficient manner. A conceptual description of the control logic is shown in Fig. 1. The logic consists of three principal steps. Initially, future temperature conditions are predicted. Next, an optimal opening strategy based on the cooling operation is determined in the second step. Finally, the operation of a cooling system is determined and an optimal opening strategy is conducted.

The first step, shown in Fig. 1, is to predict the future indoor temperature conditions. Using the developed ANN model, the temperature change from a certain moment to the next cycle is calculated for the four opening options of the double skin envelope, which is shown in Table 1. The second step in the process is to determine an optimal opening strategy. This optimal strategy represents the opening conditions under which (i) indoor temperature conditions are stabilized within required ranges for thermal comfort and (ii) energy savings is achieved. For example, when the cooling system is working, the optimal strategy of the openings is that which can drop the indoor temperature most significantly. If the TEMPPR of each opening strategy 1 to 4 are $-0.1 \degree C$, $-0.5 \degree C$, $0.3 \degree C$, and $-0.2 \degree C$ respectively, the optimal energy efficient strategy is number 2: close openings of the internal skin and open openings of the external skin.

The third step is to determine the operation of the cooling system based on a comparison between the specified operating range and the summation of TEMPN and TEMPPR. For example, when the cooling system is currently working and TEMPN plus TEMPPR is lower (e.g., $19.9 \degree C$) than the lower limit of the cooling range (e.g., $20 \degree C$ from $20\degree C$ to $23 \degree C$), the cooling system is predetermined to be turned off at this cycle. In addition, the openings of the surfaces follow the decision in the second step; that is, to close openings of the internal skin and open openings of the external skin.

A similar process is conducted when the cooling system does not operate. If the sum of the TEMPN and TEMPPR is higher than the high limit of the cooling range, for instance $26 \degree C$, the cooling system begins to work before the indoor air temperature actually reaches the marginal degree. This predictive operation can more stably control the indoor temperature conditions within the designated comfort range.

A conceptual comparison of temperature profiles achieved with conventional logic and ANN-based predictive logic is described in Fig. 2, which was referred to in previous studies [11–13]. The ANN-based predictive logic effectively stabilizes air temperature
within the designated range in an energy efficient way compared with the conventional logic since it operates cooling systems with more accurate prediction before the indoor air temperature actually reaches designated boundary conditions.

3. Development of an artificial neural network (ANN) model

Artificial neural networks (ANNs), which are based on a theory analogous to the human neural structure and learning process, have been successfully applied to building environmental controls. ANNs are composed of three major components, which are layers (input, hidden and output layers), neurons, and weights between neurons. Each layer is composed of neurons; in particular, neurons in the output layer produce the calculation results of the network. Weights represent the impact factors between neurons; determination of weights generally requires a training process for conducting optimal calculations before actually being applied in the system controls.

Compared to mathematical models such as proportional–integral–derivative (PID) controllers or regression models, ANN-based methods have proved their superiority in creating a more stable indoor environment and improved building energy efficiency. ANN models have provided optimal control of heating and cooling systems such as hydronic heating systems of solar buildings, radiant underfloor water heating systems, and air-conditioning systems [14–17]. In these studies, it was proved that the building thermal control systems were controlled effectively using the prediction of ANN predictions for optimal operating time and amount of heat supply and removal.

Recently, Moon et al. have developed an ANN-based thermal control logic for controlling heating, cooling, humidifying, and dehumidifying systems in buildings [12,13,18,19]. They suggested a framework for thermal control logic composed of physical conditions, thermal comfort range, energy, system operation decisions and operation of control devices. In addition, ANN models for conditioning indoor air temperature, humidity and predicted mean vote (PMV) have been developed and embedded in the thermal control logic. The performance (i.e., prediction accuracy and adaptability) of the proposed method was tested by comparison with the results of the conventional control logic in terms of thermal comfort and energy efficiency. Analysis revealed that ANN-based proposed logic provided advanced stability of the thermal conditions and proved adaptability for diverse disturbances encountered in environmental control within buildings.

3.1. Influential factors for variation of indoor air temperature

In general, indoor temperature conditions in buildings are derived by a heat transfer process that is affected by outdoor weather conditions, such as air temperature, humidity, wind speed and solar radiation, ventilation and infiltration rates, internal heat gain from occupants, lighting fixtures and equipment. A similar process occurs in double-skinned envelope (DSE) buildings although the effect of infiltration varies according to control strategies for the envelope.

Fig. 3 summarizes the influential factors relevant to the heat transfer process in double skinned envelope buildings. The major components of heat transfer are conductive heat flow through the envelope, ventilation and infiltration, solar radiation, and internal loads. The amount of heat transfer by each component is related to factors associated with the DSE buildings. These factors include outdoor, cavity and indoor air temperatures, solar radiation, size and properties of the envelope components, the opening conditions for the internal and external envelope, and the number of people, lighting and equipment conditions within the building.

Among these factors, the proposed ANN model employs outdoor air temperature, cavity temperature and indoor air temperatures, solar radiation, and the opening conditions of the internal and external envelope as input variables to calculate the indoor temperature change (TEMP\textsubscript{fg}), which is an output variable.

3.2. Initial ANN model

The initial ANN model shown in Fig. 4 was developed in this study using Matlab and a neural network toolbox shown in Table 2 [20]. The initial number of input, hidden and output layers was 1, and the number of neurons in each layer input, hidden and output

<table>
<thead>
<tr>
<th>Factors Relative to the Heat Transfer</th>
<th>Heat Transfer Components</th>
<th>Result of the Heat Transfer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outdoor Air Temperature</td>
<td>Conduction through Envelope</td>
<td>Change of the Interior Air Temperature</td>
</tr>
<tr>
<td>Cavity Air Temperature</td>
<td>Ventilation/Infiltration</td>
<td></td>
</tr>
<tr>
<td>Indoor Air Temperature</td>
<td>Solar Radiation</td>
<td></td>
</tr>
<tr>
<td>Solar Radiation</td>
<td>Internal Loads</td>
<td></td>
</tr>
<tr>
<td>People, Lighting, and Equipment Conditions</td>
<td>Size/Property of Envelope Components</td>
<td></td>
</tr>
<tr>
<td>Size/Property of Envelope Components</td>
<td>Surface Opening Conditions</td>
<td></td>
</tr>
</tbody>
</table>

**Table 2** Descriptions of the initial ANN model.

<table>
<thead>
<tr>
<th>Layer composition</th>
<th>Training Methods</th>
<th>Transfer Functions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of input neurons: 7</td>
<td>Learning rate: 0.75 [14,24]</td>
<td>Hidden neurons: tangent sigmoid</td>
</tr>
<tr>
<td>(i) interior air temperature: −10 to 40 °C</td>
<td>Momentum: 0.9 [14,24]</td>
<td>Output neurons: pure linear</td>
</tr>
<tr>
<td>(ii) interior air temperature change from preceding cycle: −10 to 10 °C</td>
<td>Algorithm: Levenberg–Marquardt [12–14]</td>
<td></td>
</tr>
<tr>
<td>(iii) exterior air temperature: −20 to 40 °C</td>
<td>Number of data sets: 121 using N\textsubscript{data}=(N\textsubscript{in}−(N\textsubscript{in}+N\textsubscript{out})/2)^2 [14]</td>
<td></td>
</tr>
<tr>
<td>(iv) cavity air temperature: −20 to 80 °C</td>
<td>Training goals: 0.01 K\textsuperscript{2} for air temperature (MSE)</td>
<td></td>
</tr>
<tr>
<td>(v) solar radiation: intensity on the vertical surface, 0–1100 W/m\textsuperscript{2}</td>
<td>Epoch: 1000 times</td>
<td></td>
</tr>
<tr>
<td>(vi) opening conditions of inner surface: closed: 0, opened: 1</td>
<td>Data managing technique: sliding-window method</td>
<td></td>
</tr>
<tr>
<td>(vii) opening conditions of outer surface: closed: 0, opened: 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of hidden neurons: 15 using N\textsubscript{h} = 2 \times N\textsubscript{i} + 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(vIII) opening conditions of outer surface: closed: 0, opened: 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of output neuron: 1 (TEMP\textsubscript{fg})</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
layer was 7, 15 and 1, respectively. Fifteen hidden layers were chosen based on the equation in Table 2. The output of the model was the amount of temperature rise or drop (\(\text{TEMP}_{PR}\)) from this control cycle to the next. In this study, a control cycle is defined as 5 min.

Environmental factors relative to the future indoor air temperature were selected as input neurons. They are indoor temperature \((-10 \to 40^\circ \text{C})\), indoor temperature change from the preceding ten minutes \((-10 \to 10^\circ \text{C})\) [12], outdoor temperature \((-20 \to 40^\circ \text{C})\), cavity temperature \((-20 \to 80^\circ \text{C})\), solar radiation \((0-1100 \text{W/m}^2)\), and opening conditions of the internal and external envelopes (opened: 1 or closed: 0). The opening conditions of external envelope mean the opening status of inlets and outlets for inducing outdoor air to the cavity space. These inlets and outlets can be located vertically or horizontally in the cavity space.

Actual input values were normalized to have certain values between 0 and 1 using the Eq. (1) written below. The transfer functions, the initial learning methods, and the learning algorithm were chosen based on the previous studies [12,13,18,19,21,23]. In addition, 121 training data sets were prepared using the equation in Table 2, and a sliding-window method was employed as a data managing technique.

$$\frac{\text{VAL}_{\text{ACT}} - \text{VAL}_{\text{MIN}}}{\text{VAL}_{\text{MAX}} - \text{VAL}_{\text{MIN}}}$$  \hspace{2cm} (1)

For the validation of optimization processes set up in this study, field measurements were performed in an actual double skinned buildings located in Ansan, South Korea (latitude: 37° 17′, longitude: 126° 49′). The building has three floors and built in 2007. Each floor was used for experimental facilities for sustainable buildings and office space for research personnel. The appearance and layout of the double skinned building are shown in Fig. 5(a). The primary axis of the building was rotated counterclockwise by 26° from the south–north axis. The long façades of building, which were called eastern and western façade in this study, were covered with double skin envelopes. In particular, the first floor designated in Fig. 5(b) was covered with double skin envelopes and detailed section of the buildings is shown in Fig. 5(c).

The internal and external envelopes were covered with glazing completely. A cavity space with a dimension of 5.7 m (width) by 0.5 m (depth) by 3.6 m (height) existed between the internal and external envelopes. The top, bottom and side surfaces of cavity space were also blocked with glazing, so the cavity space was separated from the adjacent double skin envelope. The internal envelope consists of double pane glass which has two layers of glass and one air layer between the glasses. The thickness of glass and air layer was 6 mm, respectively. The external envelope was single pane glass which was 10 mm thick.

Four important thermal properties for glazing which were heat transfer coefficient, solar heat gain coefficient, absorption and reflection coefficient of glass were checked. Their value for internal envelope was 2.83 W/m² K, 0.755, 0.101 and 0.126 respectively. They were also 5.68 W/m² K, 0.855, 0.095 and 0.075 for external envelope, respectively. In order to control the influence of solar irradiance from outdoor into the cavity space a Venetian blinds were installed on the outside of the internal envelope. The distance and depth of each blind slat was 2.54 cm. The Venetian blind slat had no tilt angle and covered all surfaces of internal envelope in cavity space.

To control of airflow between the internal and external envelope, openings with a dimension of 0.60 m (width) by 0.35 m (depth) were installed at the center of the top and bottom of the cavity. Each opening was used for air inlet into cavity and outlet toward outdoor. The height of air inlet was 0.3 m from the ground level. The opening for the air inlet and outlet were not obstructed. The opening conditions of inlet and outlet can be used one of inputs shown in Fig. 4. At this case, both inlets and outlets were opened, thus the opening conditions of the external envelope in the ANN model was 1. Operable window installed at the internal envelope were closed during the data monitoring periods.

A conceptual depiction of the air flow through the envelope under the cavity and envelope conditions is shown in Fig. 5(c). The
air induced into the cavity space passed through the cavity and exhausted naturally due to the buoyancy effect. In order to create identical flow conditions for the optimization process and the performance tests of the optimized ANN model presented in Section 4, the input values of the ANN model in Fig. 4 were set to 0 (closed) and 1 (opened) respectively for the openings of air inlets and outlets on internal envelope and openings of air inlets and outlets on external envelope. The cooling system was off for entire data monitoring periods, thus the indoor temperature was influenced by surrounding thermal factors, such as outdoor temperature, cavity temperature, and solar irradiance.

Data collection was conducted daily starting in December of 2007 to examine the contribution of double skin envelope to heating and cooling loads. The daily monitoring periods were from 00:00 to 24:00, and the monitoring interval was 1 min. Outdoor air temperature, cavity temperature, and indoor temperature were measured to investigate temperature profiles during the monitoring periods. Outdoor horizontal and vertical irradiance, outdoor illuminance levels were also measured to examine the impact of solar irradiance on temperature variation. All measured data were saved by an automatically equipped data logger and transferred to a computer system for further analysis.

Data monitored on July 28th, 2008 from the eastern side of the building were used as the 121 sets of training data for the initial ANN model. The number of the training data sets was derived from the Eq. (2). In addition, a sliding-window method was adopted as a data managing technique. Using the sliding-window method, the oldest set was removed when new training data set was added. By adding new set and removing oldest set, the model can be trained to reflect the latest inputs and output more effectively. Since this process repeats whenever a new training data set is produced, the ANN model can reflect the status quo more clearly.

\[ N_d = \left( \frac{N_h - (N_i + N_0)}{2} \right)^2 \]
4. Optimization and performance tests of the ANN model

4.1. Optimization of an ANN model

Indoor temperature of space in buildings generally varies according to the control strategies that determine target setting options for the space under various outdoor weather conditions. When indoor temperature of any space adjacent to double-skinned buildings is controlled, opening conditions for air inlet and outlet where air passes through should be included into the setting options. In this study, the control options for the double skin envelope are determined based on the ANN model. Hence, it is a very critical process to find an optimized ANN model that provides accurate control conditions, since the indoor temperature and energy efficiency are determined based on the output from the ANN model.

In order to produce output more accurately, the structure and learning methods of the initial model were optimized for four parameters, which were the number of hidden layers, the number of neurons in the hidden layers, the learning rate and moment, based on the method conducted in the previous study [24]. Root mean square (RMS), mean square error (MSE), and maximum difference between the predicted value from the ANN model and the measured data in the actual building with a double skin envelope were parametrically compared. For this, 288 data sets were collected on July 29th, 2008 in the building. After deriving an optimal value for one parameter, the weights of neurons in the ANN model were initialized before conducting an optimization process for the next parameter in order to avoid the results being affected by the previous optimization process.

The first step of the optimization was conducted to determine the number of hidden layers. Tests were parametrically performed for numbers from 1 to 10. During the tests, other parameters such as the number of neurons in the hidden layers (15), learning rate (0.75), and moment (0.90) were fixed as initial values. Instead of applying the adaptive learning rate to the model, the learning rate was fixed to 0.75 based on optimization process, in which the learning rate 0.75 supported the best performance of the ANN model. Fig. 6 compares the root mean square (RMS) of errors of ANN-predicted values from the monitored data. Overall, all models present a stable RMS (<0.015 K), however the optimal number of hidden layers was determined to be 6 with a 0.00779 K RMS value and a 0.00006 K² MSE. The maximum positive and negative differences of this case were 0.22358 K and −0.30280 K, respectively.

The second step was to determine the optimal number of neurons in the hidden layers through a series of parametrical tests with different numbers of neurons in the hidden layer. A variation from 10 to 20 neurons in the hidden layers was applied while the newly found optimal number of hidden layers (6), the initial learning rate (0.75), and moment (0.90) were fixed. In Fig. 7, the RMS of errors between predicted and monitored values were compared for each case. The lowest value occurred for 13 neurons with 0.00719 K (RMS) and 0.00005 K² (MSE), and its maximum errors were 0.32504 K and −0.32515 K. Thus, the optimal number of neurons is 13.

The third step of the optimization process was conducted to find optimal learning rates. A series of learning rates from 0.00 to 1.00 by increments of 0.05 were tested with a fixed number of hidden layers (6), number of neurons in the hidden layers (13), and moment (0.90). Fig. 8 proves that the optimal learning rate was 0.60, which provided the smallest 0.00577 K (RMS) and 0.00003 K² (MSE). The maximum positive and negative differences were 0.28965 K and −0.35789 K.

The last process was to optimize the learning moment. Similar to the learning rate, moments from 0.00 to 1.00 were tested in increments of 0.05. During the tests, the number of hidden layers (6), number of neurons in the hidden layers (13), and the learning
rate (0.60) were all fixed, as given from the previous steps. Fig. 9 compares the results and the optimal case was determined to be a 0.40 moment, which provided the lowest values of RMS and MSE, i.e., 0.00515 K and 0.00003 K$^2$, respectively. The maximum positive and negative differences were 0.29358 K and −0.37464 K.

As shown in the results, the MSE and RMS values of every case were much smaller than the training goal of the ANN model (0.01 K$^2$ of MSE). The optimal structure and the learning method of the developed ANN model for predicting future indoor temperature conditions determined in this study were 6 hidden layers, 13 neurons in the hidden layers, a 0.60 learning rate, and a 0.40 moment. Through the performance tests described in the following section, this optimized ANN model proves its potential for optimum control logics that effectively keep energy-efficient indoor temperature conditions.

4.2. Outdoor irradiance and temperature of cavity space

Field measurements in this study were conducted for an entire year to examine the influence of a double skin envelope on heating and cooling load. Among a variety of data monitored in an actual building, data from August 10th to August 11th were selected for a discussion in this study since the two days showed typical clear and partly cloudy sky conditions in the summer.

Figs. 10 and 11 show the variation of outdoor solar irradiance for clear and partly cloudy sky conditions. For the clear sky condition, the overall global horizontal irradiance was stable and the variations constituted a symmetrical pattern for a day. The irradiance increased stably and reached a maximum value of 863.84 W/m$^2$. The maximum vertical irradiance values that reached the external envelope for the eastern and western façades were 504.47 W/m$^2$ and 623.01 W/m$^2$, respectively. Irradiance on the western envelope was higher than that for the eastern envelope due to the continuous accumulation of direct and diffused irradiance from the sun and sky surface.

For the partly cloudy sky conditions, where the sun is frequently blocked by clouds and then exposed again, the global irradiance showed unstable variation. Due to the orientation of the building and solar altitude, the variation ranged widely. The maximum variation for horizontal irradiance was 670.90 W/m$^2$. For the eastern and western envelope, the maximum change ranges of vertical irradiance for a minute were 369.06 W/m$^2$ and 264.73 W/m$^2$, respectively.

The variation of irradiance for each envelope under various sky conditions resulted in a change in cavity temperature. Temperature variations in the cavity under clear and partly cloudy sky conditions are shown in Figs. 12–15. Generally, the variation patterns of cavity temperature were similar to those of vertical solar irradiance in the envelope. The temperature of the air outlet positioned at the top of the cavity showed the highest values when outdoor air entered the cavity from the bottom of the double skin envelope. This result occurred because the air was influenced by the accumulated irradiance in the cavity, while the air passed through the cavity space.

Under clear sky conditions, when the outdoor temperature for the air inlet ranged from 24.53 °C to 35.82 °C, the maximum temperature at the center of the cavity was 40.4 °C and 43.9 °C for the eastern and western envelopes, respectively. The cavity temperature for the eastern and western envelopes under the partly cloudy sky conditions ranged from 25.2 °C to 40.7 °C and from 25.2 °C to 39.3 °C respectively, when the outdoor air at the air inlet position varied from 24.89 °C to 34.58 °C. In summary, the temperature in the cavity space functioned as a thermal buffer zone between the
indoor space and the outdoor space, and was significantly influenced by the solar irradiance and outdoor air temperature.

4.3. Performance of the ANN model

The performance of the optimized ANN model was tested by comparison with actual data measured from the double skin building and ANN predicted values. For this, checking data sets were collected from the east and west side of the existing double skin envelope modules for clear sky conditions (August 10, 2008) and partly cloudy sky conditions (August 11, 2008). After determining the validity of the ANN model performance, the optimized ANN model could be employed in the developed indoor air temperature control logic.

The RMS and MSE between the measured values and \( \text{TEMP}_{\text{PR}} \) determined by the ANN model for eastern and western sides under clear sky conditions are shown in Fig. 16. For the 288 checking processes, field measurements and prediction values showed similar results. The maximum positive and negative differences of the east and west sides were 0.4330 K and −0.3760 K, and 0.4045 K and −0.4784 K, respectively.

In addition, in 98.6% and 93.8% of cases, the difference between predicted and monitored values (difference in \( \Delta \text{Temperature} \) between the measurements and ANN predictions) for the eastern side was within ±0.3 K. These differences were 0.0128 K RMS and 0.0002 K\(^2\) MSE for the eastern side, and 0.0270 K RMS, 0.0007 K\(^2\) MSE for the western side, which were much less than the designated training goal (0.01 K\(^2\)). This result implies that the optimized ANN model predicted future temperature conditions accurately as intended. Values for the eastern side were slightly less than those of the western side because the ANN model was tuned using the training data collected from the east.

The RMS and MSE between the measured and predicted values for partly cloudy sky conditions are shown in Fig. 17. All values varied stably within the training goal with 0.0139 K, 0.0002 K\(^2\) for the east side and 0.0259 K, 0.0007 K\(^2\) for the west side. The maximum differences were 0.2632 K, −0.3834 K and 0.3431 K and −0.4673 K, thus 98.6% and 95.8% of the differences were within ±0.3 K, respectively.

The validity analysis of the developed ANN model using RMS, MSE, and the difference of predictions with the monitored value revealed that the developed ANN model successfully predicted the future indoor temperature conditions. Differences were significantly smaller than the training goal for all cases, i.e., different sky conditions and orientations. Thus, the developed ANN model provides not only prediction accuracy, but also adaptability to the different building background conditions. Based on these findings, the ANN model in this study can be successfully applied to the developed temperature control method for double skin envelope buildings under various weather conditions.

5. Conclusion

This study examines optimum control strategies for double skin envelope to maintain energy-efficient indoor thermal environment based on artificial neural network. An ANN model was developed to achieve the control strategies for the operation of air inlets and outlets of a double skin envelope and a cooling system. The structure...
and learning methods of the developed ANN model were parametrically optimized. Also, the validity of the optimal model was demonstrated through the comparison between the predicted values by the ANN models and the actual data monitored from the double skin building. By employing the developed ANN model in this study, further study is necessary to develop an expanded control method that can be applied for summer, winter and interim season since the data used in this study were limited to winter conditions. Their performance needs to be fully tested under diverse weather conditions to achieve accurate control strategies for indoor thermal environments in buildings with a double skin envelope. For this test, the performance of control logics for opening options and thermal control devices should be examined in future study in terms of thermal comfort and energy-efficiency. A summary of findings in this study is as follows.

(1) Through the parametrical process, the developed ANN model was optimized for four parameters. Thus, it is comprised of 6 hidden layers, 13 neurons in the hidden layers, a 0.60 learning rate, and a 0.40 moment.

(2) The prediction accuracy of the ANN model for indoor temperature was proved by the significantly smaller RMS and MSE values than the training goals. This accuracy supports the applicability of the proposed ANN model.

(3) The adaptability of the ANN model was proven with stable RMS and MSE values for the diverse applications. These results indicate that the ANN model successfully conducted the self-tuning process, thus, the model could be adaptively applied to various building conditions without expert intervention. The results of this study imply that the developed ANN model has potential to be successfully applied to the temperature control method for buildings with double skin envelope systems in summer.

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