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Research paper

Comparative performance analysis of the artificial-intelligence-based thermal control algorithms for the double-skin building

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HIGHLIGHTS

- Integrated control algorithms were developed for the heating system and surface openings.
- AI theories were applied to the control algorithms.
- ANN, FL, and ANFIS were the applied AI theories.
- Comparative performance tests were conducted using computer simulation.
- AI algorithms presented superior temperature environment.

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ABSTRACT

This study aimed at developing artificial-intelligence-(AI)-theory-based optimal control algorithms for improving the indoor temperature conditions and heating energy efficiency of the double-skin buildings. For this, one conventional rule-based and four AI-based algorithms were developed, including artificial neural network (ANN), fuzzy logic (FL), and adaptive neuro fuzzy inference systems (ANFIS), for operating the surface openings of the double skin and the heating system. A numerical computer simulation method incorporating the matrix laboratory (MATLAB) and the transient systems simulation (TRNSYS) software was used for the comparative performance tests. The analysis results revealed that advanced thermal-environment comfort and stability can be provided by the AI-based algorithms. In particular, the FL and ANFIS algorithms were superior to the ANN algorithm in terms of providing better thermal conditions. The ANN-based algorithm, however, proved its potential to be the most energy-efficient and stable strategy among the four AI-based algorithms. It can be concluded that the optimal algorithm can be differently determined according to the major focus of the strategy. If comfortable thermal condition is the principal interest, then the FL or ANFIS algorithm could be the proper solution, and if energy saving for space heating and system operation stability is the main concerns, then the ANN-based algorithm may be applicable.

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1. Introduction

The artificial-intelligence-(AI)-based control strategy has been increasingly proposed for creating advanced building environmental quality. As AI theories are applied in the control process, the building indoor environmental quality is controlled in predictive and adaptive ways for improved environment and energy efficiency. Artificial neural network (ANN), fuzzy, and adaptive neuro fuzzy inference system (ANFIS) are the representative theories that are successfully employed for advanced building controls [1–3].

Employing the input, hidden, and output neurons in the respective layers and the connectivity and transfer functions between them, ANN can produce the optimal output for advanced building controls. Its prediction results were proven to be more accurate than those of mathematical models like the proportional-integral-derivative (PID) controllers, or of regression models. In addition, the adaptability via a self-tuning process supports the stability of the model without external expert intervention for the retuning model parameters [4,5].

ANN models were developed for predicting the optimal stop and start moments of the heating and cooling systems. Employing these

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Nomenclature

$TEMP_{IN}$	Indoor air temperature, °C
$\Delta TEMP_{IN}$	Indoor air temperature change from the preceding control cycle, °C
$TEMP_{CAV}$	Cavity air temperature, °C
$TEMP_{OUT}$	Outdoor air temperature, °C
$TEMP_{PR}$	Indoor temperature predicted by the ANN model, °C
$INPUT_{ACT}$	Actual input value
$INPUT_{MIN}$	Minimum input value
$INPUT_{MAX}$	Maximum input value
U	Heating system operating ratio, unitless
U_{NEW}	U of the current cycle, unitless
U_{OLD}	U of the previous cycle, unitless
U_{TRN}	U for the new training dataset, unitless
E	Difference between the current air temperature and the set point temperature, °C
ΔE	Change in E from the previous cycle, °C
T_H	Set point temperature for the heating system, °C
T_{NEW}	Temperature in the current control cycle, °C
n_i	Number of input neurons
n_h	Number of hidden neurons
n_o	Number of output neurons
n_d	Number of datasets

calculated values, the ANN-based models created a more comfortable and energy-efficient indoor thermal environment [6–8]. The applicability of the ANN model was presented for the hydronic heating systems of solar buildings with significant energy savings [9,10]. In addition, the ANN-based control methods effectively controlled the HVAC systems and the radiant water heating systems that have a significant time lag [11–14].

Using the degree of truth or falsity of phenomena, fuzzy logic (FL) has been successfully applied in building environment controls based on their benefit of not requiring precise and noise-free input data for proposing the control signals [15].

A fuzzy model that employed two inputs — (i) the difference between the current temperature and the set point temperature (E); and (ii) the difference between the current E and the previous E (ΔE) — created a better output for operating HVAC systems compared to the proportional–integral (PI) or PID controllers [16]. In addition, a fuzzy-based PMV control strategy provided more comfortable PMV conditions as well as temperature and humidity conditions in a highly energy-efficient manner [17–19]. More recently, a radiant heating system in a residential building was successfully controlled by FL incorporated with the ANN model [20]. Moreover, FL was applied to condition the whole-building environment, such as the thermal, lighting, and air quality [21,22].

In order to overcome the difficulty of FL for finding optimized rules and membership functions, ANFIS can be applied to building environmental controls. ANFIS, a neuro-fuzzy theory, adopts FL and ANN in an incorporative manner for developing a globally applicable control method. As with FL, ANFIS employs a series of inputs and membership functions to produce an output. In addition, the membership functions are iteratively updated to produce a more accurate output using output errors, which is similarly conducted in the ANN model. This iterative tuning process supports the ANFIS model to optimally respond to the given systems and buildings [1,2].

In the previous study, the ANN and ANFIS models were comparatively tested for controlling evaporative condensers. In this study, the ANFIS models showed slightly superior results in terms of predicting condenser performance [23]. In other studies, the ANFIS model successfully operated the damper gap rate and fan speed in the HVAC system for faster, simpler, and more efficient temperature and humidity control [24,25]. In addition, in the comparative tests of ANN, FL, and ANFIS, the ANFIS-based model controlled the indoor temperature more comfortably and stably [3].

For the creation of a comfortable and energy-efficient indoor thermal environment for double-skin buildings, an AI-based control strategy was proposed in the previous studies [26–30]. The openings of the internal and external surfaces of the double skin and the heating system were operated in an integrative manner based on the prediction results from two ANN models. One model predicted the optimal opening strategy for keeping the indoor space comfortable, and the other model calculated the accurate operating ratio of the heating system. Compared to the conventional rule-based control method, the thermally comfortable period was remarkably increased with temperature stability when the ANN models were used for controlling the thermal condition of the double-skin building. On the other hand, energy efficiency for heating was not clearly demonstrated, resulting in a similar or lower efficiency.

Based on the findings of the previous studies, this study aimed at investigating the diverse AI-theories-based optimal control strategies for improving the thermal conditions and heating energy saving effect of double-skin buildings. Besides the ANN models proposed in the previous studies, FL and ANFIS were applied in the control algorithms, and their performances were comparatively analyzed. The comparison results would clearly show the optimal control strategy in terms of indoor thermal conditions and heating energy efficiency.

2. Development of the control algorithms

Algorithms for the integrative control of the heating system and the surface openings were developed. In the previous studies [29,30], the ANN-based surface control algorithm proved its superiority for the advanced thermal environment; thus, the ANN model was applied for surface opening control in the new algorithms in this study. On the other hand, FL and ANFIS models were applied for the control of the heating system. In particular, two ANFIS models with two input variables and one input variable, respectively, were developed and tested. Thus, performance analysis was conducted for five control algorithms, as summarized in Table 1. The algorithms were developed using the matrix laboratory (MATLAB) software and its relevant toolboxes, such as the neural network toolbox and the fuzzy logic toolbox [31].

2.1. Rules for the heating system and ANN for surface openings (1st algorithm)

The first algorithm, which employs a specific rule for operating the heating system and the ANN model for operating openings, is shown in Fig. 1. In a specific rule for deciding the heating system operation, the current operating condition, current temperature

Table 1
Five control algorithms with different theories.

	Applied theories	
	For heating system	For surface openings
1st algorithm	Rule	ANN
2nd algorithm	ANN	ANN
3rd algorithm	FL	ANN
4th algorithm	ANFIS with 2 inputs	ANN
5th algorithm	ANFIS with 1 input	ANN

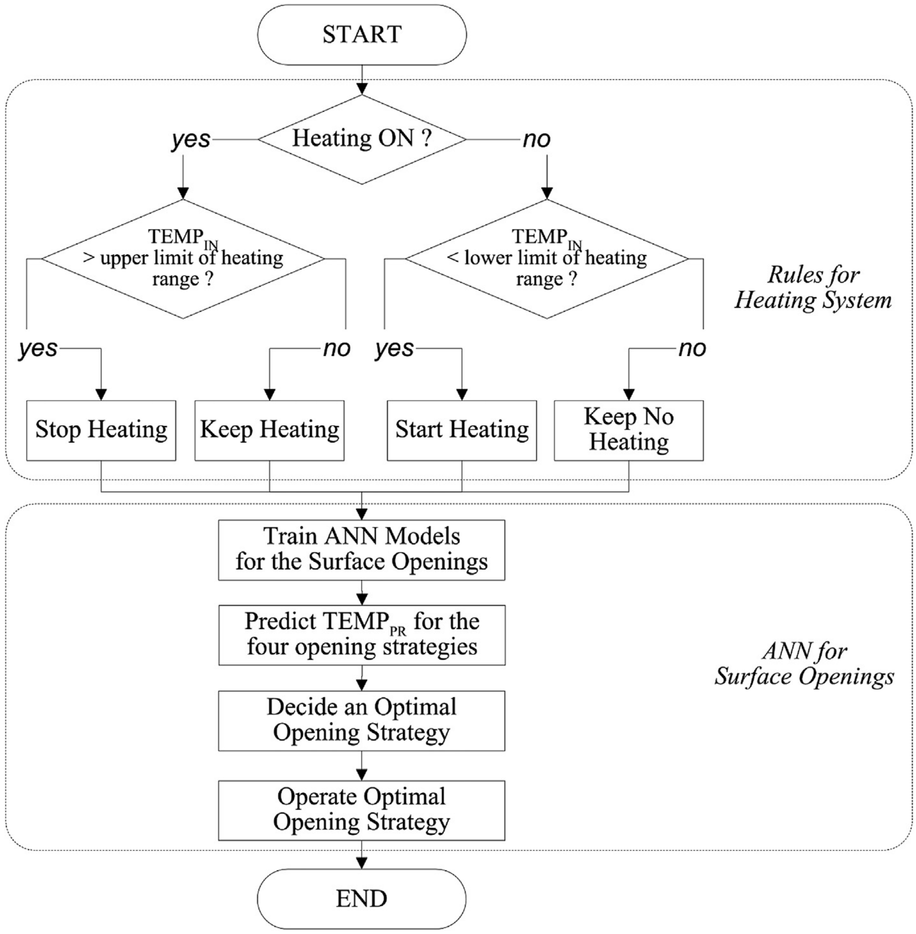

Fig. 1. Flow of the 1st algorithm.

($TEMP_{IN}$), and operating range of the heating system were used as determinants. For example, if the heating system is currently working and the $TEMP_{IN}$ is over the upper limit of the heating range, the rule turns off the heating system.

For optimally operating surface openings, four ANN models were developed for predicting the future indoor temperature ($TEMP_{PR}$). Each ANN model calculates the $TEMP_{PR}$ for the four opening cases: (i) the openings on both surfaces are closed; (ii) the internal openings are closed and the external openings are open; (iii) the internal openings are open and the external openings are closed; and (iv) the openings on both surfaces are open. Based on the comparison of the predicted values, the optimal opening

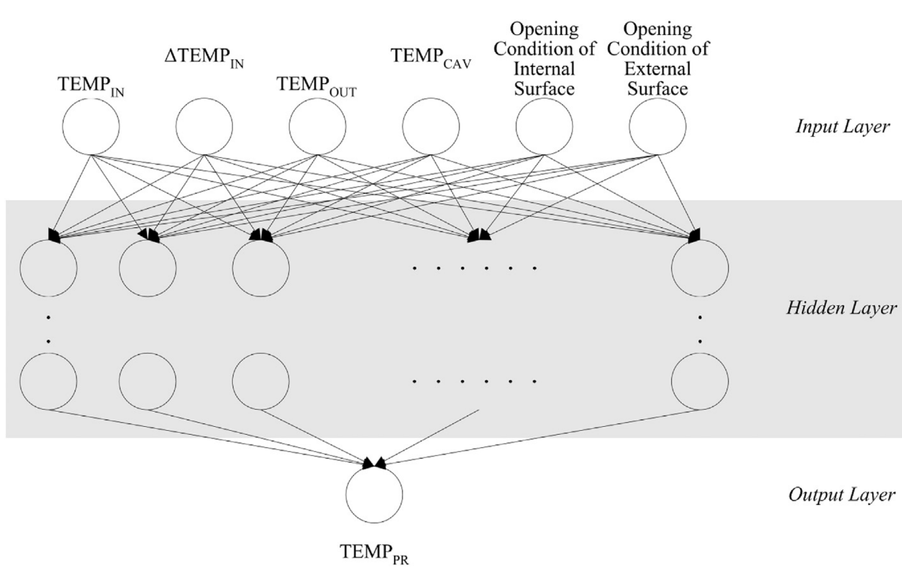

Fig. 2. ANN model for surface openings.

Table 2
Training parameters of the ANN model for the surface openings.

Training methods [29]	• Algorithm: Levenberg–Marquardt • Learning rate: 0.75 • Moment 0.30 • Training goals:0.01 K^2 for air temperature (MSE) • Epoch: 1000 times • Number of data sets: 85
Training data management technique [29,33,34]	A sliding-window method

strategy is determined, and the surface openings will follow the determined strategy. For example, if the $TEMP_{PR}$ values are +2.0, −1.5, +1.5, and −2.5 °C, respectively, for the four cases, then the optimal opening strategy is the 1st case, where the openings of both surfaces are closed.

The structure of the ANN models for predicting $TEMP_{PR}$ is shown in Fig. 2. One input layer, 10 hidden neurons in the four hidden layers, and one output layer comprise the ANN model, in which the number of hidden neurons and layers were optimally derived in previous studies [26,29,30].

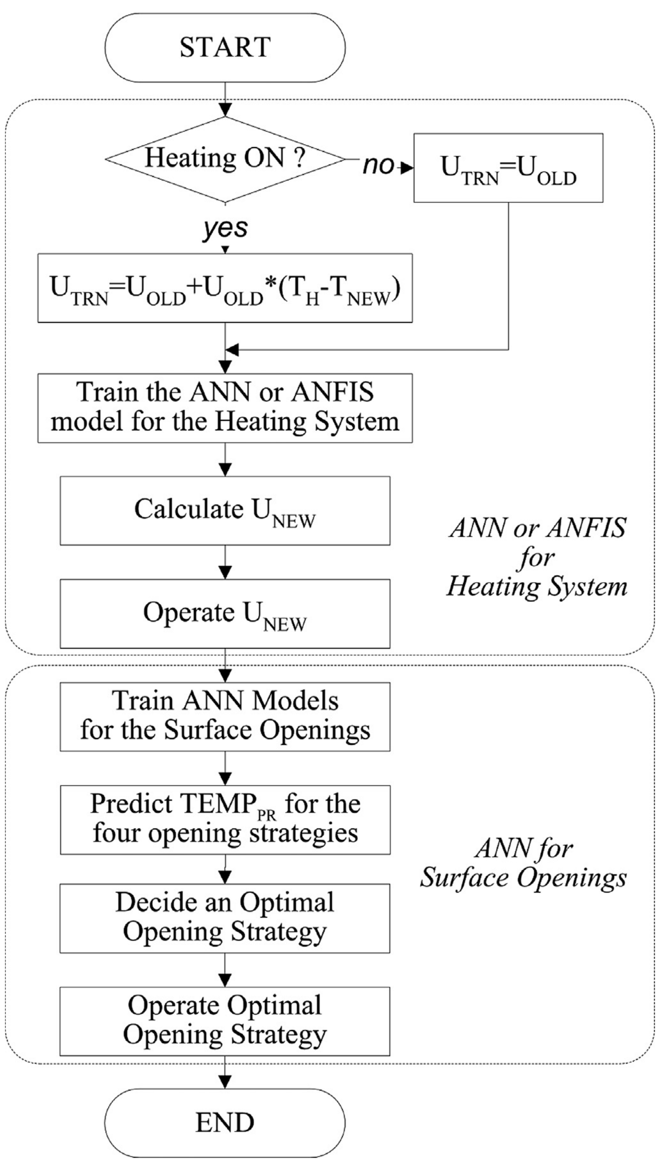

Fig. 3. Flow of the 2nd, 4th, and 5th algorithms.

The components of the input neurons were deeply related to the conductive and convective heat transfer process between the indoor and outdoor spaces. The actual values of the input components were −10–40 °C for $TEMP_{IN}$, −10–10 °C for $\Delta TEMP_{IN}$, −20–40 °C for $TEMP_{CAV}$, and −20–80 °C for $TEMP_{OUT}$, 0 (closed) and 1 (open) for the surface opening conditions. Using Equation (1), the first four input values were normalized to have a number between 0 and 1. The tangent sigmoid and pure linear methods, which are commonly applied in backpropagation multilayer networks, were employed as the transfer functions for the hidden and output neurons, respectively [26,29,30].

$$INPUT = (INPUT_{ACT} - INPUT_{MIN})/(INPUT_{MAX} - INPUT_{MIN}) \quad (1)$$

The parameters for the iterative training of the ANN models are summarized in Table 2. The Levenberg–Marquardt algorithm was used for training with a 0.75 learning rate and a 0.30 moment, which were found to be the optimal values in the previous study [29]. The training goal and epoch that were assigned were 0.01 K^2 for the air temperature, and 1000 times. Based on Equation (2) [29], 85 datasets were obtained from the computer simulation using MATLAB and TRNSYS [32], which will be explained in section 3. In addition, a sliding-window technique was used for the training dataset management; thus, the oldest dataset was removed when the new datasets were acquired [29,33,34].

$$n_d = (n_h - (n_i + n_o)/2)^2 \quad (2)$$

2.2. ANNs for the heating system and surface openings (2nd algorithm)

The second algorithm employed ANN models for controlling both the heating system and the surface openings, as shown in Fig. 3. The first ANN model calculated the operating ratio of the heating system, and the second ANN model was used to find the thermally optimal opening strategy identical to that in the first algorithm.

The first ANN model, which was designed to calculate the operating ratio (U), presented a continuous-basis ratio between 0 and 1 for operating the heating system. The structure of the ANN

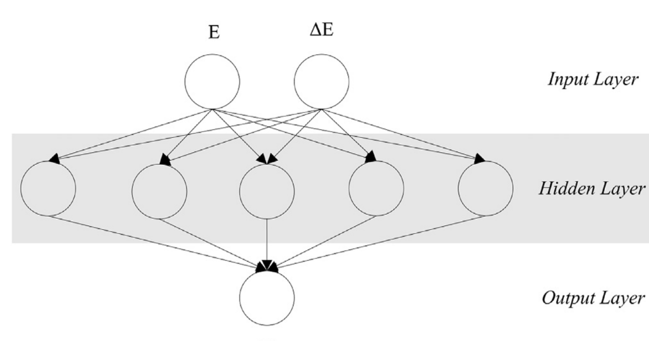

Fig. 4. ANN model for heating system [3,29].

Table 3
Training parameters of the ANN model for the heating system.

Training methods [35]	• Algorithm: Levenberg–Marquardt • Learning rate: 0.75 • Moment 0.90 • Training goals:0.00 K^2 for U (MSE) • Epoch: 1000 times • Number of data sets: 25
Training data management technique [32,35]	A sliding-window method

model is shown in Fig. 4. One input layer, a hidden layer, and an output layer comprised it. In the input layer, two neurons (E and ΔE) were employed, respectively, representing the difference between the indoor air temperature and the set point temperature, and the changing amount of E from the previous cycle. The number of neurons in the hidden layer was determined as five based on Equation (3) [29]. The tangent sigmoid and pure linear transfer functions were applied for the hidden and output neurons, respectively.

$$n_h = 2 \times n_i + 1 \quad (3)$$

The parameters for the training model are summarized in Table 3. As with the model for the surface openings, the Levenberg–Marquardt algorithm was applied with a 0.75 learning rate, a 0.90 moment, a 0.00 K^2 goal, and a 1000 times epoch, based on the findings of the previous study for the optimal calculation [3]. Using the previously mentioned Equation (2), 25 datasets were prepared for training the ANN model. In addition, the sliding-window method was applied for data management. The process for training the ANN model and for calculating the U of the heating system is summarized in Table 4.

2.3. *FL for the heating system and ANN for surface openings (3rd algorithm)*

The third algorithm employed an FL model for controlling the heating system, and ANN models for operating the surface openings, as shown in Fig. 5. The ANN models employed for the surface openings were identical to those that were used in the first algorithm. Thus, the same process was carried out for optimally operating the surface openings.

The FL model, which was developed for the heating system, employed two input variables — (i) the difference between the air temperature and the set point temperature (E); and (ii) the change in E from the previous cycle (ΔE) for calculating the heating system operating ratio (U). The membership functions shown in Fig. 6 were tuned for calculating the optimal output in the previous study [3].

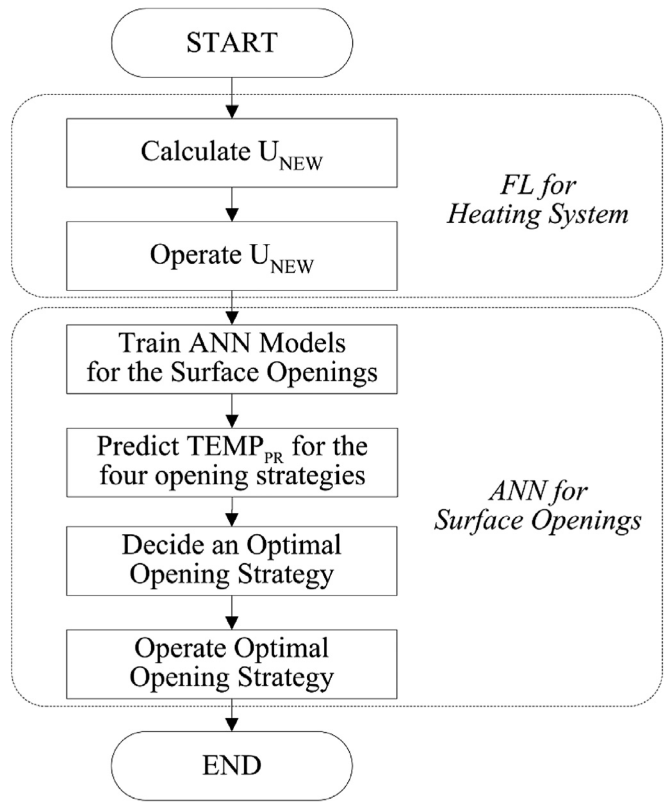

Fig. 5. Flow of the 3rd algorithm.

Trapezoidal and triangular shapes were employed for the membership functions, with ranges between −2.0 and 2.0 °C for E, −2.0 and 2.0 °C for ΔE, and −1.0 and 1.0 for U. As the range of U was set between −1.0 and 1.0, the values derived from this range were designed to be converged to −1.0 and 1.0. The fuzzy if–then rules are summarized in Table 5.

Table 4
Process for training ANN model and calculating U.

Processes		Descriptions	Examples
(1)	Find U_{TRN}	Using equation $U_{TRN} = U_{OLD} + U_{OLD}*(T_H - T_{NEW})$	When the set-point temperature is 21.5 °C, $TEMP_{IN}$ is 21.2 °C, and U of the heating device during the previous cycle is 0.3, then U_{TRN} is determined to be 0.39. This means that U of the previous cycle should have been 0.30 in the previous cycle.
(2)	Find E_{OLD} and ΔE_{OLD}	Using the $TEMP_{IN}$ of the previous cycle and of the two cycles	If $TEMP_{IN}$ of the previous cycle and of the two cycles before it are 20 °C and 19.9 °C, respectively, then E_{OLD} is −1.5 °C (20–21.5 °C) and ΔE_{OLD} is 0.1 °C ((20°–21.5 °C)–(19.9–21.5 °C)).
(3)	Add $E_{OLD,}$ ΔE_{OLD}, and U_{TRN} in the new training datasets	Using the sliding-window data management technique, the new set is added to the training datasets, replacing the oldest.	–
(4)	Train the ANN model	Using the new training datasets	–
(5)	Calculate U_{NEW} for the current cycle	Using the trained ANN model	–

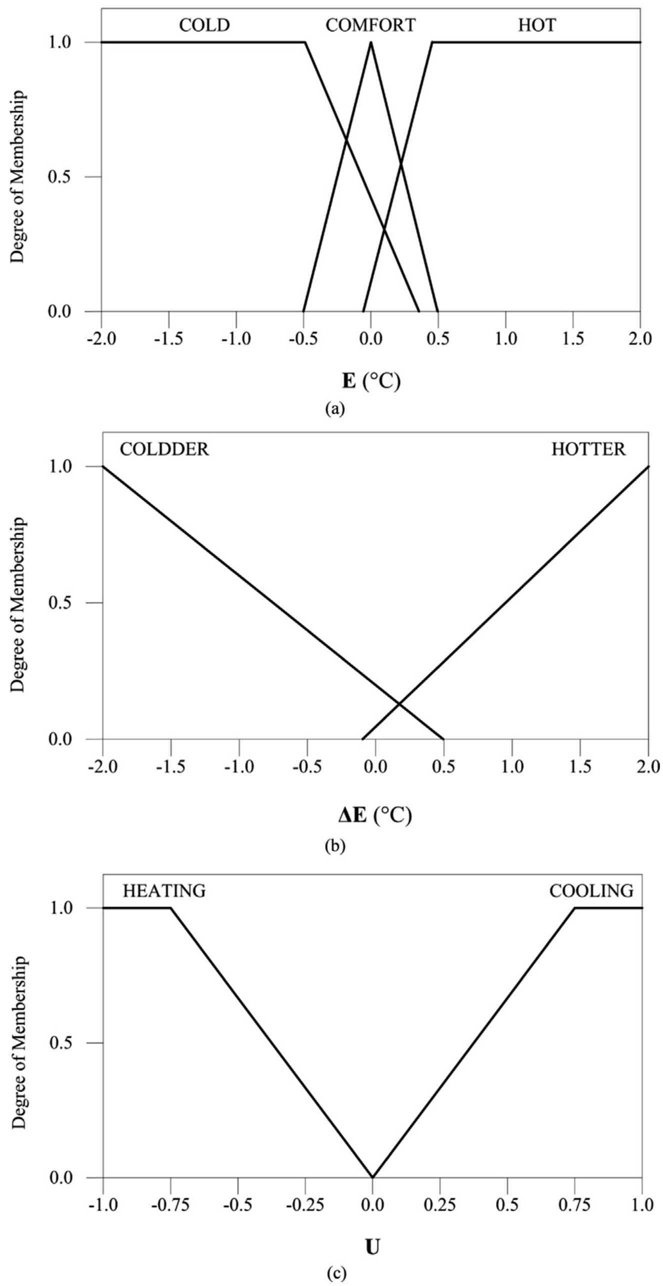

Fig. 6. (a) Membership function plots of E (1st input), (b) membership function plots of ΔE (2nd input), (c) membership function plots of U (output).

2.4. ANFIS for the heating system and ANN for the surface openings (4th and 5th algorithms)

The fourth and fifth algorithms, which are identical to the second logic shown in Fig. 3, employed an ANFIS model with different input variables for controlling the heating system, and ANN models for operating the surface openings. As with other algorithms, the surface opening conditions were determined by the ANN models.

Two Sugeno-type ANFIS models with two inputs (E and ΔE) and one input (E), respectively, were applied to the fourth and fifth algorithms, respectively. Each model produced a variable output U for the heating system. The applied output membership functions and rules are summarized in Tables 6 and 7.

The iterative training process, which was identical to the ANN model in the second algorithm (Table 4), was carried out for adjusting the parameters of the output membership functions. Thus, the model can produce the optimal output (U) for the changing environment. Similar to the ANN model, training datasets that added new input and output sets were used for the training. For the training process, most of the parameters of the training model followed the recommended values in the fuzzy logic toolbox of MATLAB. Thus, 30 epochs, 0.0 error tolerance, a 0.01 initial step size, a 0.9 step size decrease rate, a 1.1 step size increase rate, the back-propagation training method, and 40 training datasets were employed [3,31].

Table 6
If–then rules and functions of ANFIS with 2 input variables [3].

Inputs (if)			Outputs (then)
E		ΔE	U
Cold	And	Colder	Output membership function 1
Cold	And	Hotter	Output membership function 2
Comfortable	And	Colder	Output membership function 3
Comfortable	And	Hotter	Output membership function 4
Hot	And	Colder	Output membership function 5
Hot	And	Hotter	Output membership function 6

3. Performance tests

The performances of the five algorithms were comparatively tested to investigate the algorithms' influence on the indoor thermal conditions and building energy efficiency. A one-story test building with a double skin was modeled for the numerical simulation, as shown in Fig. 7. The building was 4.2 m wide, 4.5 m deep, and 3.05 m high, and it was covered with south-facing double-skin envelopes. The cavity depth was 0.9 m, with an air inlet and an air outlet at the top and bottom on both the internal and external envelopes. Each opening was 0.3 m high and 0.5 m wide.

The thermal resistance values (R-value) of the roof, walls, floor, and internal and external glazings were 5.00, 2.78, 2.44, 0.77, and 0.18 m^2K/W, respectively. The internal load consisted of two seated occupants carrying out light office tasks, two computers with printers, and 5 W/m^2 lighting fixtures. Convective heat transfer occurred through ventilation and infiltration with 0.7 ACH (air change rate per hour). No shading devices and external obstructions were considered around the test building. For space heating, a radiative heating system with a 7172 kJ/h heat supply capacity was installed. The TMY2 weather data were employed for Seoul, South Korea (latitude: 37.56°N; longitude: 126.98°E). The performance

Table 5
Fuzzy if–then rules [3].

Inputs (if)			Outputs (then)
E		ΔE	U
Cold	And	Colder	Heating
Cold	And	Hotter	Heating
Comfortable	And	Colder	Heating
Comfortable	And	Hotter	Cooling
Hot	And	Colder	Cooling
Hot	And	Hotter	Cooling

Table 7
If–then rules and functions of ANFIS with 1 input variable [3].

Input (if)	Outputs (then)
E	U
Cold	Output membership function 1
Comfortable	Output membership function 2
Hot	Output membership function 3

tests for the five algorithms were conducted for the heating season from January 1 to March 31.

The performance tests were conducted using the TRNSYS [32] and MATLAB [31] software in an incorporative manner, as shown in Fig. 8. The TRNSYS components that were employed for the simulation are summarized, along with their roles, in Table 8. In particular, the type 155 component linked the MATLAB-based control algorithm to the TRNSYS model.

The validity of the simulation method was proven in previous studies [33,36], in which the indoor temperature collected from an actual building was statistically compared with the simulated indoor temperature calculated by the simulation model. The analysis results showed a significant relationship between the collected and simulated values; thus, the validity of the simulation method for testing the performances of diverse control algorithms was proven.

Table 8
Employed TRNSYS components and roles.

Components	Roles
Type 9c	Reading the TMY2 weather file
Type 16a	Calculating the amount of solar radiation on the test building surface
Type 69b	Calculating the sky temperature
Type 33e	Calculating the outdoor dew-point temperature
Type 56a-TRNFlow	Calculating the indoor temperature of the test building
Type 155	Connecting the MATLAB and ANN models
Type 65d-2	Producing the output file

4. Results analysis

4.1. Profile of temperature and system operation

The operation profile of the surface openings and the heating system as well as the indoor, outdoor, and cavity temperature conditions for the five algorithms for the sample period of January 1–10 are shown in Fig. 9. The cavity temperature of the double skin was conditioned between the indoor and outdoor temperatures. In particular, the temperature in the cavity space was significantly higher than the outdoor air temperature during the day, when the solar radiation caused the cavity air to rise.

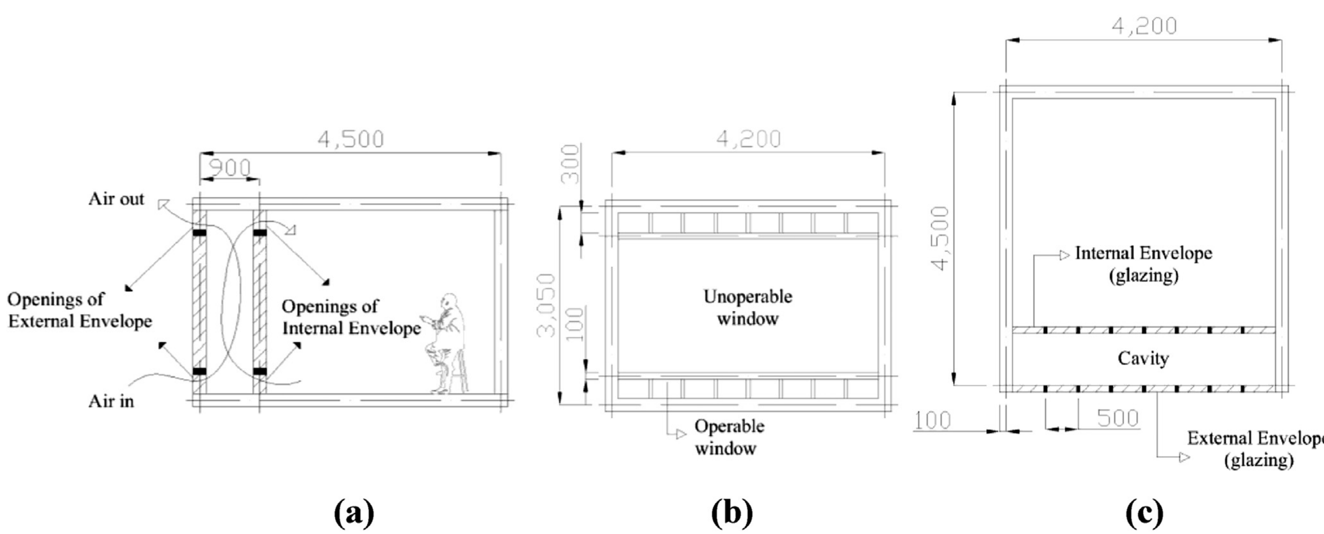

Fig. 7. Test building, (a) section, (b) front elevation, (c) plan, unit: mm [37].

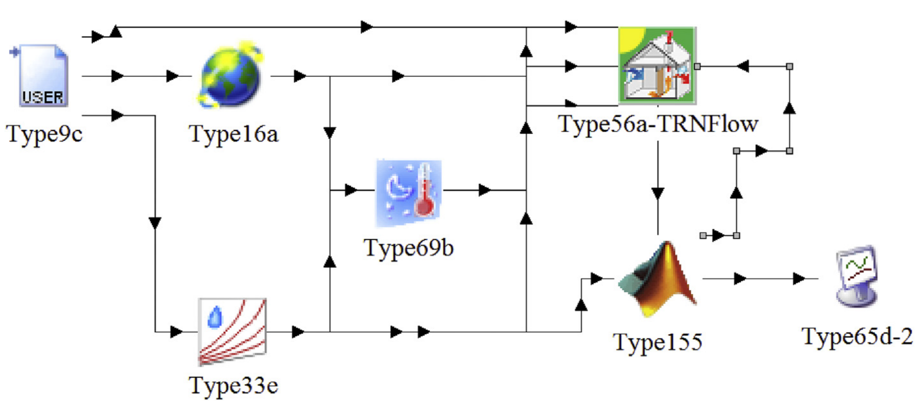

Fig. 8. Composition of the simulation model [37].

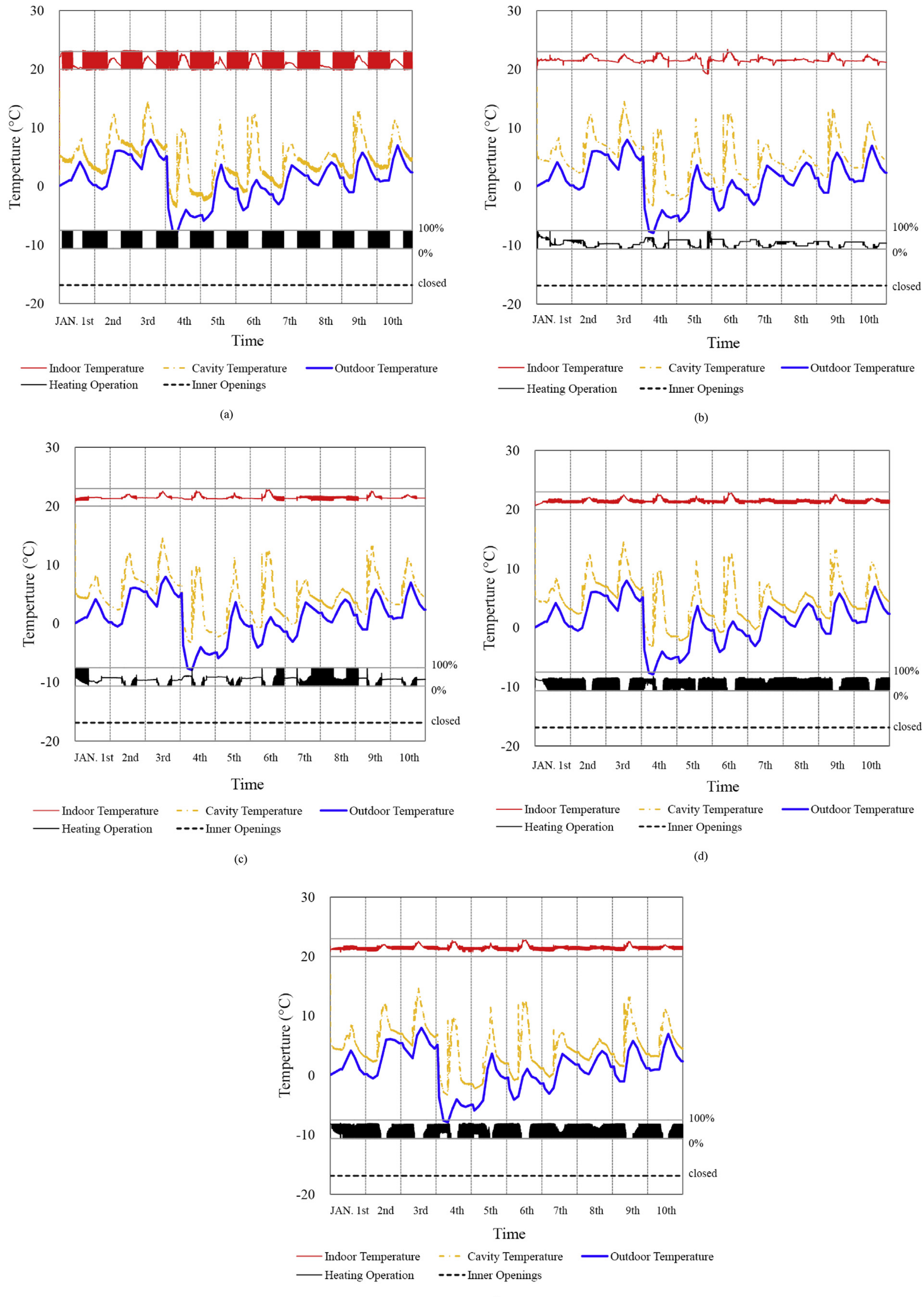

Fig. 9. Profile of temperature and system operation: (a) Rule–ANN; (b) ANN–ANN; (c) FL–ANN; (d) ANFIS with 2 inputs–ANN; and (e) ANFIS with 1 input–ANN.

The openings of the internal surface were closed by all the algorithms for the whole sample period. This was due to the prediction results of the ANN-based algorithm that determined the closing of the internal surface openings as an optimal method for controlling the indoor temperature conditions. During the whole test period, the openings of the external surface were set to be closed for blocking the outdoor air to the cavity space.

The rule-based heating system control method (1st algorithm) repeatedly turned the heating system on and off, following the designed two-position rule, as shown in Fig. 9(a). As a result, the indoor temperature fluctuated between the maximum and minimum values of the operating range (20–23 °C). On the other hand, the four other algorithms, which employed a variable heating system and AI theories for finding the optimal operation ratio (U), changed the operating ratio from 0 to 1. Therefore, the indoor temperature was closely maintained around the center of the operating range (21.5 °C), with less fluctuation (Fig. 9b–e). In particular, the second algorithm, which employed the ANN model for variable heating system control, operated the heating system with the least changing ratio; thus, the small-scale fluctuation of the indoor temperature was reduced.

4.2. Indoor temperature conditions

The indoor temperature condition results of the five algorithms are summarized in Table 9. The indoor temperature was conditioned slightly higher when the AI theories were applied to the control algorithm. The differences with the rule-based heating system control algorithm were 0.43, 0.27, and 0.30 °C for the ANN-, FL-, and two-ANFIS-based algorithms, respectively. This was due to the variable controls of the heating system using the calculated operation ratio U. Similar to the indoor temperature, the cavity air temperature slightly rose when the AI-based algorithms were applied, due to the increased heat transfer from the indoor space with a higher temperature.

The standard deviation (SD) values of the indoor temperature from the center (21.5 °C) of the operating range (20–23 °C), and the average temperature, were significantly reduced when the AI theories were applied in the control algorithm. Compared to the rule-based algorithm, the reduction percentage was 13.28, 42.19, 39.06, and 39.83% when the SD was calculated using the center of the operating range, and 15.58, 72.74, 40.50, and 41.43%, respectively, for the four AI-based algorithms. This means that the air temperature created by the AI models was better stabilized even though small-scale fluctuation occurred iteratively at around 21.5 °C.

The period of comfortable temperature condition was also significantly increased when the FL and ANFIS models were applied. Compared to the rule-based algorithm, the amount of increase was as much as 2.92, 2.61, and 2.73% for FL, ANFIS with two inputs, and ANFIS with one input, respectively. In particular, no cold period occurred when FL or ANFIS was used for calculating the optimal operating ratio (U).

On the other hand, the period over the comfortable range was increased when the U was calculated by the ANN model. For much of the hot period, the U for the heating system was calculated to be close to 0 by the ANN model. Thus, the uncomfortably hot conditions were not caused by the heating system operation but by the thermal inertia of the indoor space. For a similar reason, the ANN-based heating system control algorithm significantly reduced the cold period compared to the rule-based algorithms.

4.3. Heating system operation

The heating system operation results of the five algorithms from January 1 to March 31 are summarized in Table 10. The AI-theory-based algorithms presented the possibility of consuming more energy for space heating. Compared to rule-based heating system control, the AI algorithms supplied a greater amount of heat to the indoor space. The increase amounts were 3.97, 8.42, 11.48, and 16.45% for the algorithms from the 2nd to the 5th. This has a connection to the fact that the AI-based heating system control methods keep the indoor temperature higher than that of the rule-based method. Similarly, the average heating system operating ratio (U) was greater when the four AI theories were applied.

The changing ratio of U was significantly reduced, however, when the AI theories were applied. The SDs from the average ratio and 0.5, which is half of the heating capacity, all decreased. This means that the heating system worked stably, with less fluctuation. In particular, the ANN-based algorithm reduced the SD from the average and 0.5 by as much as 80.34 and 56.00%, respectively, compared to the rule-based algorithm. Thus, the ANN model showed the potential of operating the heating system most stably.

In addition, the ANN and FL models reduced the number of on/off moments of the heating system compared to the rule-based method. The reduced number reached 14,864 and 222, respectively. The ANN-based algorithm significantly reduced the on/off moments, meaning the stability of the system operation. The reduced on/off moments can in the long run reduce the system degradation caused by the iterative and frequent turning on/off of the system.

From the analysis of the indoor temperature conditions and the heating system operation, it was revealed that the AI-based algorithms increased the overall indoor temperature and the comfortable period in most cases, except the 2nd algorithm, which employed an ANN model for operating the heating system. In this case, the thermal inertia was the major reason for the increase in the hot period, over the comfortable range. In addition, the ANN-based heating system control algorithm proved its potential to be the most energy-efficient and stable strategy among the four AI-based algorithms.

Table 9
Indoor temperature conditions created by the five algorithms.

			Algorithms				
			ANN–Rule	ANN–ANN	ANN–FL	ANN–ANFIS with 2 inputs	ANN–ANFIS with 1 input
Temperature (°C)	Average	Indoor	21.53	21.95	21.80	21.83	21.83
		Cavity	6.67	6.71	6.70	6.70	6.70
	Standard deviation	From 21.5 °C	1.284	1.108	0.741	0.781	0.769
		From the average temperature	1.284	1.084	0.350	0.764	0.752
Thermal environment (%)	Cold		2.90	0.88	0.00	0.00	0.00
	Comfortable		85.85	83.68	88.77	88.46	88.58
	Hot		11.25	15.44	11.23	11.54	11.42

Table 10
System operation by five algorithms.

		Algorithms				
		ANN–Rule	ANN–ANN	ANN–FL	ANN–ANFIS with 2 inputs	ANN–ANFIS with 1 input
Amount of heat supply (kWh)		1537.28	1598.31	1666.68	1713.85	1790.17
Operating ratio (U)	Average	0.214	0.222	0.231	0.238	0.249
	Standard of deviation from the average	0.168	0.033	0.048	0.082	0.101
	Standard of deviation from 0.5	0.250	0.110	0.121	0.151	0.163
Number of heating system on/off (times)		15,046	182	14,824	34,032	35,922

5. Conclusions

The aim of this study was to develop AI-based optimal control strategies for providing comfortable indoor temperature conditions and for saving heating energy of double-skin buildings. One conventional rule-based algorithm as a base-case and four AI-based algorithms were developed, including ANN, FL, ANFIS with two inputs, and ANFIS with one input. Using a numerical computer simulation method incorporating the MATLAB and TRNSYS, comparative performance tests were conducted. Results analysis was conducted for the profile of the temperature and system operation, indoor temperature conditions, and heating system operation. The findings are summarized below.

(1) The indoor temperature was conditioned slightly higher when the AI theories were applied to the control algorithm, due to the variable control of the heating system using the calculated operation ratio (U).
(2) The period of comfortable temperature condition was significantly increased when the FL and ANFIS models were applied. In particular, no cold period occurred when FL or ANFIS was used for calculating the optimal operating ratio (U).
(3) The hot period, over the comfortable range, was increased when the ANN model was used for calculating U. This, however, was caused by the thermal inertia of the indoor space. The ANN-based heating system control algorithm significantly reduced the cold period compared to the rule-based algorithms, for a similar reason.
(4) The standard deviation (SD) values of the indoor temperature were significantly reduced when the AI theories were applied in the control algorithm. This supports the stability of the indoor temperature with the AI-based control method.
(5) The AI-theory-based algorithms supplied more heat from the indoor space compared to the rule-based heating system control algorithm. Similarly, the average U of the heating system was greater when the AI theories were applied.
(6) The changing ratio of U was significantly reduced, however, when the AI theories were applied, with lower SD values. This finding supports the stability of the system operation. In particular, the ANN-based algorithm reduced the SD most significantly.
(7) In addition, the ANN-based algorithm significantly reduced the on/off moments, meaning the stability of the system operation. The reduced on/off moments can in the long run reduce the system degradation caused by the iterative and frequent turning on/off of the system.

The analysis results revealed that the advanced comfort and stability of the thermal environment can be provided by the AI-based algorithms. In particular, the FL and ANFIS algorithms were superior to the ANN algorithm in terms of providing better thermal conditions with the increased comfortable period and the decreased SD values, but the ANN-based heating system control algorithm proved its potential to be the most energy-efficient and stable strategy with the smaller amount of heat supply and the decreased number of on/off of the heating system among the four AI-based algorithms.

The findings in this study showed similar analysis results for the thermal conditions with the previous study in which three AI-based control logics – ANN, FL, and ANFIS were compared their performance [3]. In the previous study, the comfortable period over the lower limit of the designated comfortable range was most successfully provided by the ANFIS logic followed by FL and ANN, which is identical result with this study. However, compared to the findings in the previous study, in which the amount of heat supply was very similar by three AI-based logics, the ANN-based algorithm in this study showed superiority over the other three AI-based algorithms.

Based on the findings in this study and the comparisons with the previous study, it can be concluded that the optimal algorithm can be differently determined based on the major focus of the control strategy. If comfortable thermal condition is the principal interest, then FL or ANFIS could be the proper solution, and if energy saving for the space heating and stability of the system operation are the main concerns, then ANN may be applicable. However, further study is warranted for the deeper investigation on the energy saving effect of the algorithms.

This study was conducted for proposing a diverse AI-based algorithm for the heating season. Further study is required for developing an algorithm for the cooling and interim seasons. In addition, a comprehensive algorithm that consolidates diverse seasonal algorithms needs to be developed. In the future study, the actual data after application to the real building should be acquired and analyzed to support the validity of the proposed algorithm.

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