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Influence of control logic on variation of indoor thermal environment for residential buildings

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Abstract

This study proposes an advanced thermal control method that employs artificial neural network (ANN) models for predictive and adaptive thermal control. Two predictive and adaptive control logic approaches were proposed to simultaneously control indoor temperature and humidity as well as predicted mean vote (PMV) in a residential building. Their thermal performance was analysed and compared with that of non-ANN-based counterparts to evaluate architectural variables such as envelope insulation and building orientation. A numerical computer simulation method was used for the tests after demonstration of its validity based on comparison with results of field measurement. Analysis results revealed that the proposed predictive and adaptive control methods conditioned the indoor temperature, humidity and PMV effectively. The periods during which each thermal factor was in a comfortable range increased, and overshoots and undershoots out of the targeted comfortable ranges were reduced when using the ANN model. The results demonstrate the functionality of the proposed method for variation in architectural variables and that the ANN model has the potential to be successfully applied to building thermal controls.

Keywords

Thermal control method, Artificial neural network, Predictive and adaptive control logic, Residential building, Envelope insulation, Building orientation

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Introduction

Indoor thermal environments of residential buildings are typically controlled by simple methods such as thermostats. Thermostat control systems, which use current temperature and user-specified set-point temperature for heating and cooling systems, have been widely applied to the control of indoor temperature conditions. In general, a thermostat controls heating and cooling systems based on on–off control settings, under which heat is provided to an indoor space or removed from an indoor environment.

However, with an increased awareness of quality of life concerns, comfort and health issues regarding indoor environments have become important factors that should be considered more prudently.[1] Indoor environmental quality needs to be precisely and synthetically controlled to satisfy user demands for better conditions of indoor thermal environments.

As a result of new thermal requirements in buildings, residential thermal control strategies are changing from conventional methods to a new method, as shown in Figure 1. The conventional control strategy is independent, static and inflexible, whereas the new control strategy is integrated, dynamic and flexible.

First, instead of independent control of the heating, cooling, humidifying, and dehumidifying systems,

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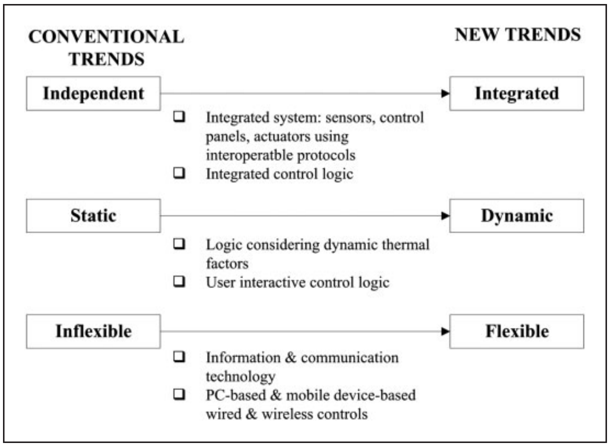

Figure 1. Changing trends in residential thermal controls.[2]

the new control strategy employs integrated systems and logic using interoperable protocols. Second, in order to improve static features in the conventional method, the new thermal control strategy employs dynamically changing thermal factors in the control algorithm and responds interactively to user intervention. Finally, the new strategy flexibly controls the thermal environment using the information and communication technology of wired or wireless approaches. Access to the control domain is possible for multiple users from multiple locations.[2]

A good control strategy that meets requirements for the new control method is the artificial neural network (ANN), which is analogous to the human neural structure and its learning process.[3] ANN-based control has been applied to thermal controls for buildings because of its outstanding predictability and adaptability.[4–16] Thermal control strategies using ANN models are superior to conventional mathematical methods such as regression models or proportional–integral–derivative methods.

In previous studies, the ANN-based control method provided more comfortable and stable temperature conditions with improved energy efficiency for heating and cooling systems.[4–10] In particular, predictive control methods exhibited outstanding performance when used to operate thermal control devices that had a long time lag, such as radiant water heating systems.[11–13]

In other studies, ANN-based thermal control logic for residential buildings was applied to determine the optimal control of heating, cooling, humidifying and dehumidifying devices.[14,15] The performance of the ANN-based temperature, humidity and predicted mean vote (PMV) control methods was compared with that of non-ANN counterparts. Results of these analyses indicated that ANN-based predictive control could control temperature, humidity and PMV more stably within comfortable ranges. In addition, the ANN-based control logic showed a significant energy saving effect for the heating, ventilation and air-conditioning (HVAC) systems.[16]

The proposed ANN-based control methods are expected to meet new requirements for residential thermal controls. Since ANN-based control logic can be embedded in an integrated control system framework using a microcontroller, the data acquired by sensors regarding dynamically variable factors can be considered in the control logic. Optimal output signals for the thermal control devices, which are calculated by the ANN model, will provide more comfortable and stable thermal conditions. In addition, this control logic can be freely accessed by multiple users from multiple locations using communication networks in order to satisfy their various thermal requirements.

In previous studies, the performance of ANN-based thermal control methods was tested using variables such as user requirements (application of setback and change of set-point temperature for thermal control devices) and disturbances (variation in infiltration rate, internal loads, and climate conditions).[14,15] However, the proposed ANN-based thermal control methods still have to be fully tested in a range of buildings. This study proposes and tests ANN-based predictive and adaptive thermal control methods for residential buildings in four research phases.

First, ANN-based predictive thermal control methods were developed to control indoor thermal conditions including air temperature, humidity and PMV. Second, measurements were completed in a mock-up chamber space and the measured data were compared with numerically simulated data to demonstrate the validity of the numerical simulation method.

Third, after validity tests of the numerical simulation method, the prediction accuracy of the developed ANN model was analysed using comparison between values predicted by the ANN model and simulated values. Finally, thermal performance of the proposed ANN-based control methods and conventional non-ANN-based control methods was tested for architectural variables such as variation in envelope insulation and orientation of the building. The thermal conditions for the proposed and conventional methods were analysed in terms of comfortable periods and magnitudes of overshoot and undershoot.

Development of ANN-based thermal control logic and ANN models

Two methods of ANN-based control logic and two methods of non-ANN-based control logic were developed in this study to examine the influence of control logic on indoor thermal environment. The control logic approaches are (i) temperature and humidity control with ANN, (ii) PMV control with ANN, (iii) temperature and humidity control without ANN and (iv) PMV control without ANN.

Figures 2–4 show the algorithms that employ the ANN model for control of temperature, humidity and PMV. The ANN models in each algorithm predict

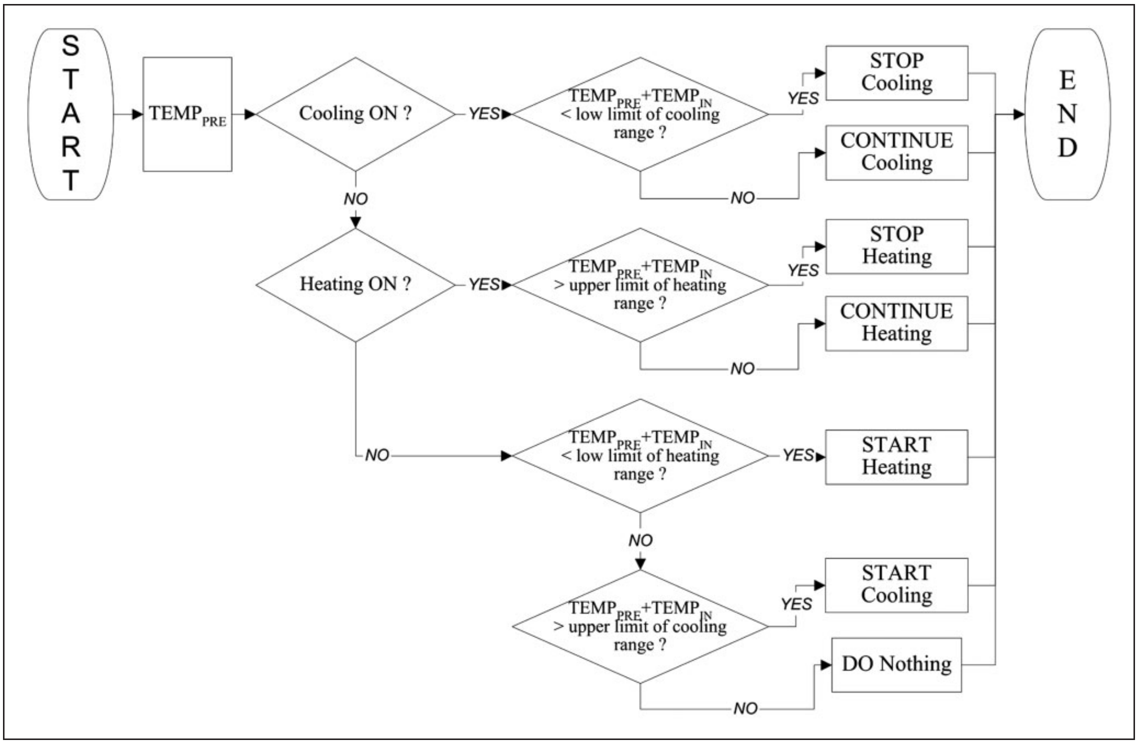

Figure 2. ANN-based temperature control logic.

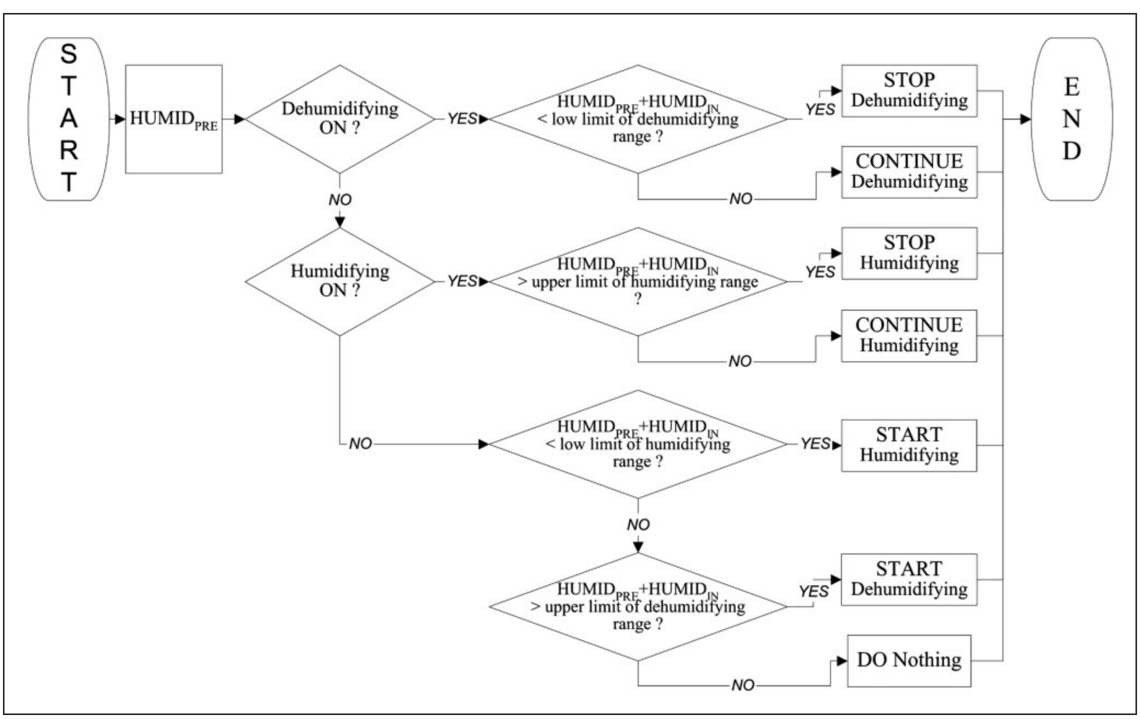

Figure 3. ANN-based humidity control logic.

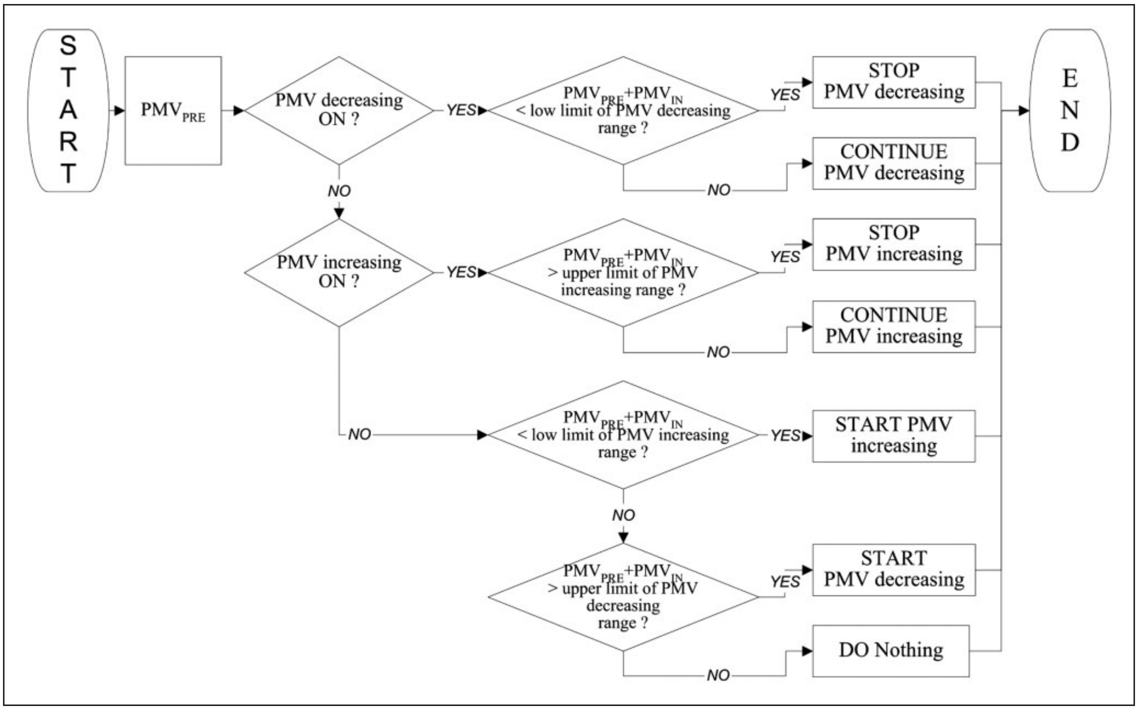

Figure 4. ANN-based PMV control logic.

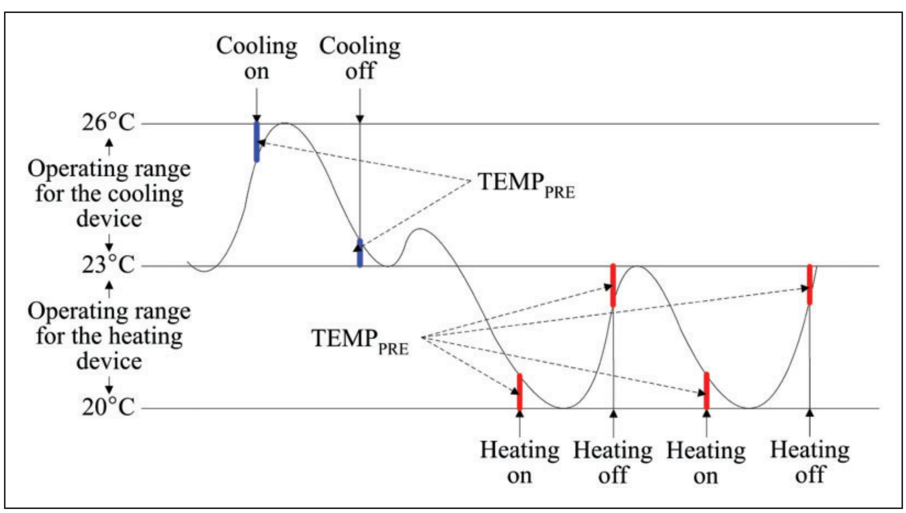

Figure 5. Indoor temperature profile by ANN-based temperature control logic.

the amount of overshoot or undershoot for temperature ($TEMP_{PRE}$), humidity ($HUMID_{PRE}$) and PMV (PMV_{PRE}), which refers to the maximum amount of increase or decrease, respectively, when the operating mode of the control device is changed. For example, in winter, $TEMP_{PRE}$ is the maximum rise in temperature after the heating device is turned off. These predicted values were used with the current conditions, such as temperature ($TEMP_{IN}$), humidity ($HUMID_{IN}$) and PMV (PMV_{IN}) to operate thermal control devices.

Because of its predictive approach, the control logic effectively stabilises thermal factors within designated ranges. Figure 5 conceptually shows the indoor temperature profile when the predicted values were used in the control logic. The operation of cooling and heating devices is predetermined for the given operating ranges.

Three ANN models were developed to predict overshoot or undershoot of temperature ($TEMP_{PRE}$, °C), humidity ($HUMID_{PRE}$, %) and PMV (PMV_{PRE}) in residential buildings. Two ANN models for predicting $TEMP_{PRE}$ and humidity $HUMID_{PRE}$ were used in temperature and humidity control logic with ANN, and the last ANN model for predicting PMV_{PRE} was employed in PMV control logic with ANN. Since the occupants' activity level (MET) and clothing level (CLO) were used for calculating PMV, the PMV-based logic is expected to satisfy the individual's thermal requirement more concisely and dynamically. For testing performance of the logic, specific values for MET and CLO were applied.

Each ANN model consists of one input layer, one hidden layer and one output layer. The input layer is composed of eight neurons, indoor air temperature ($TEMP_{IN}$, °C), indoor air temperature change ($\Delta TEMP_{IN}$, °C), outdoor air temperature ($TEMP_{OUT}$, °C), outdoor air temperature change ($\Delta TEMP_{OUT}$, °C), indoor relative humidity ($HUMID_{IN}$, %), indoor relative humidity change ($\Delta HUMID_{IN}$, %), relative humidity ($HUMID_{OUT}$, %), and outdoor relative humidity change ($\Delta HUMID_{OUT}$, %). $\Delta TEMP_{IN}$ and $\Delta HUMID_{IN}$ represent the amount of change in the preceding 10 min, and $\Delta TEMP_{OUT}$ and $\Delta HUMID_{OUT}$ represent the change in the preceding hour. The ranges of each input neuron are summarised in Table 1. The input variables are normalised to have values between 0 and 1 using equation (1).

The number of hidden neurons is 17 based on equation (2). The output layer employs one neuron that is the calculation result of the ANN model. Each model calculates $TEMP_{PRE}$, $HUMID_{PRE}$ and PMV_{PRE}, respectively. Tangent sigmoid and pure linear transfer functions were, respectively, employed in the hidden and output neurons.

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

$$N_h = 2 \times N_i + 1 \quad (2)$$

Table 1. Ranges of input neurons.

Neuron (N_i)	Range
i) TEMP	−10–40°C
ii) $\Delta TEMP_{IN}$	−10–10°C
iii) $TEMP_{OUT}$	−20–40°C
iv) $\Delta TEMP_{OUT}$	−20–20°C
v) $HUMID_{IN}$	0–100%
vi) $\Delta HUMID_{IN}$	−10–10%
vii) $HUMID_{OUT}$	0–100%
viii) $\Delta HUMID_{OUT}$	−50–50%

where $INPUT_{ACT}$ is actual input value; $INPUT_{MAX}$ is maximum input value; $INPUT_{MIN}$ is minimum input value, N_i is the number of input neurons; and N_h is the number of hidden neurons.

Values for the learning rate (0.75), moment (0.30), training goal (0.01 K^2 for air temperature) and epoch (1,000 times) were consistent with values obtained in the optimisation process in previous studies.[4–6] In addition, the Levenberg–Marquardt algorithm was used for training the ANN model. In total, 75 training data sets were used for the model training based on equation (3) and the sliding-window method was applied to manage the training data.

$$N_d = (N_h - (N_i + N_o)/2)^2 \quad (3)$$

where N_d is the number of training data sets and N_o is the number of output neurons.

Thus, when a new training data set was acquired, the new data set replaced the oldest set in order to better reflect the latest conditions in the ANN model. The time required for the training and prediction using a standard laptop computer was minimal less than three seconds at maximum.

As counterparts to the two ANN-based control logics, two non-ANN-based logics were developed. Those were temperature and humidity control without ANN, and PMV control without ANN. They did not employ any ANN models for predicting overshoot and undershoot of thermal factors such as temperature, humidity and PMV. Thus, the operation of the thermal control systems (e.g., heating, cooling, humidifying and dehumidifying systems) was determined, when the thermal factors went out of the operating range resulting in an increased thermally uncomfortable period. These two non-ANN-based logics were comparatively tested with two ANN-based logics.

Research method

In this study, two major processes were adopted to effectively compare the performance of the control methods. The first step was to validate the simulation software in order to provide reliable grounds for further simulations in several thermal situations of buildings. The simulation results for a building using developed control logic were compared with field measurement data monitored from a mock-up chamber, which was built with thermal properties equal to those used for the simulations.

Next, computer simulations were performed using control logic for a variety of building conditions in order to examine the influence of thermal control logic on the indoor thermal environments of residential buildings. ANN-based control logic and non-ANN-based control logic were used for the simulations.

Validation of simulation software

For the validation procedure, field measurements were conducted in the mock-up chamber shown in Figure 6. The mock-up chamber was located in a high-bay space of a university building with a main façade facing south. The major envelope of the chamber was adjacent to the south-facing envelope of the university building. The remaining envelopes of the chamber were exposed to the indoor environment surrounded by a high-bay space.

Two windows were installed on the east and south envelopes. The dimensions of the south-facing window were 2.85 m × 0.9 m, and the bottom line of the window was 1.2 m from the floor. The dimensions of the east-facing window were 0.9 m × 0.9 m, and the bottom line of the window was 1.1 m from the floor. The south-facing window was covered with rigid insulation panels to block solar radiation and prevent its effects on indoor thermal conditions.

The insulation levels for walls were 3.8, 3.6, 1.8, and 0.18 m^2K/W for north, east, south and west walls, respectively. The roof and floor contained 3.6 and 3.7 m^2K/W of insulation. The windows installed on south and east walls had insulation levels of 0.4 m^2K/W. The infiltration rate of the chamber was assumed to be 1.0 air change rate per hour (ACH).

A thermal control system was installed for data monitoring and device control. This system included sensors, a data acquisition system, a control panel with computer hardware and control logic, and thermal control devices such as a radiant heater, air conditioner, humidifier, and dehumidifier. A radiant heating system with heat capacity of 1500 W was installed for heating, and an air-conditioning unit with 1480 Wh was used for heat removal from the chamber. To control humidity, a humidifier with a capacity of 0.00047 $m^3\ h^{-1}$ of moisture supply and a dehumidifier with a capacity of 0.00069 $m^3\ h^{-1}$ of moisture removal were installed.

A variety of sensors were used to measure temperature, air velocity, humidity and mean radiant temperature. Their accuracy was within recommended ranges and no significant deviation of accuracy occurred during the entire monitoring period. Sensors for monitoring indoor air temperature and humidity were positioned at the centre of the chamber at a height of 1.2 m which is a normal working surface. The dry-bulb temperature, relative humidity, and heating and humidifying device operation were monitored every minute.

The operating range of the heating device was 20 to 23°C based on general guidelines, under which the comfortable ranges are 20 to 23.5°C for winter and 23 to 26°C for summer.[17] Using the zero-band method,

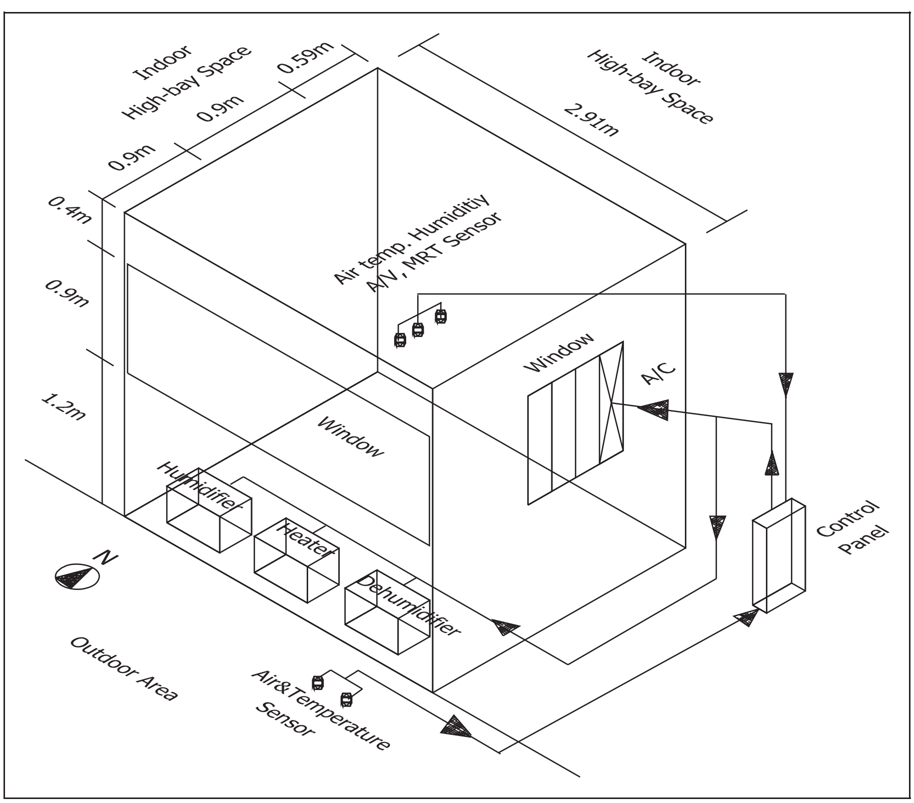

Figure 6. Layout of mock-up chamber.

the operating range of the heating system was determined to not overlap with that of the cooling system.

Simulation results were compared with field measurement results to demonstrate the validity of the proposed control logic. For effective comparison between measurements and simulations, the measurement conditions of the chamber were identically modelled in the simulation process using MATLAB (Matrix Laboratory) and IBPT (International Building Physics Toolbox).

Numerical performance simulation

After validation test procedures were completed, the performance of the developed ANN-based thermal control methods was numerically tested using Matrix Laboratory (MATLAB) and the International Building Physics Toolbox (IBPT). MATLAB was developed by MathWorks for numerical computing and programming, and its neural network toolbox was employed as the primary method for developing ANN models.[18]

In this study, MATLAB was used for (1) calculating indoor PMV, (2) developing ANN models and thermal control logic, (3) calculating $TEMP_{PRE}$, $HUMID_{PRE}$ and PMV_{PRE} from the developed ANN models and (4) determining the operation of thermal control devices using thermal control logic. The decision from the logic was fed into the IBPT to work the thermal control devices.

The IBPT was developed at the Chalmers Institute of Technology, Sweden, and is an energy simulation software package that can simulate building systems and performance.[1] It was used for (1) modelling building components and related features (e.g., envelopes, thermal control devices, initial thermal conditions, internal loads, infiltration rate and weather data), and (2) calculating indoor temperature ($TEMP_{IN}$) and humidity ($HUMID_{IN}$). By adopting the decisions from MATLAB for the operation of the devices, IBPT produced a new indoor thermal environment, which was subsequently transferred to MATLAB.

Computer simulations using control logic were performed for a typical two-storey residential building under a variety of thermal and weather conditions to examine the influence of control logic on the indoor thermal environment. The building was assumed to be located in Detroit, Michigan, USA (latitude: 42°19?N, longitude: 83°20?W). The dimensions of the test building are shown in Figure 7.

Each floor area of the test building was 92.2 m^2 and the total floor area was 184.4 m^2. The ratio of window to exterior wall on the envelope was 8, 14, 24, and 13% for north-, east-, south- and west-facing walls, respectively. The infiltration rate through the window was assumed to be 0.7 ACH.

The thermal resistance (R-value) of wall, roof, floor, windows and door was 3.35, 6.69, 3.70, 0.61, and 0.20 m^2K/W, respectively. These values were used for the boundary conditions of the base case for simulation in this study. For further simulations, the R-values of the walls, roof and windows were parametrically changed to test the developed control logic. Additionally, it

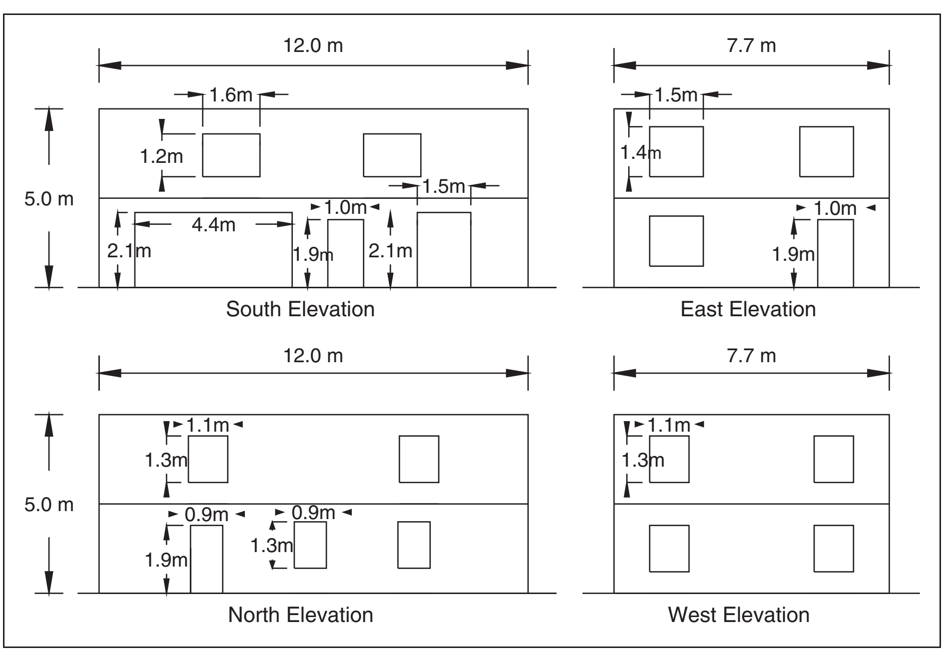

Figure 7. Layout of a tested residential building.

was assumed that the building faced south for the base case simulation. Seven additional conditions for building orientation were applied to further simulations to examine the influence of building thermal properties on the performance of the control logic.

For computer simulation, it was assumed that hourly-weighted heat and moisture gain for a family of four was applied for internal heat gain. The initial air temperature and relative humidity were assumed to be 23°C and 45%, respectively. In addition, mean radiant temperature of the test building was assumed to be equal to the indoor air temperature and no significant air movement was considered in the simulation. The occupants' activity and clothing levels were assigned to be 1.0 MET and 1.0 Clo for winter, and 1.0 MET and 0.5 Clo for summer, respectively.

The targeted thermal comfort range for air temperature, humidity and predicted mean vote (PMV) during summer was 23–26°C, 45–60%, and 0.0–0.5, respectively. Corresponding values for winter were 20–23°C, 30–45%, and 0.5–0.0, respectively. The comfortable ranges for air temperature, humidity and PMV were assigned based on existing recommendations.[17]

Thermal control devices, such as heating, cooling, humidifying and dehumidifying systems, were installed to satisfy the targeted thermal comfort ranges. A convective heating device with a heat capacity of 9000 W and a cooling device with 10,000 W of heat removal were used. For humidity control, a humidifier and dehumidifier with capacities of 1.41 kg/h and 2.36 kg/h, respectively, were used. To control PMV, the heating and humidifying devices worked together to increase PMV. Similarly, the cooling and dehumidifying devices worked together to decrease PMV.

The boundary conditions used for simulations are summarised in Table 2. The insulating level of the walls, roof and windows was parametrically tested. When the R-value of one component was changed, the R-values of the other components were kept constant as the base case. In addition, when tests were conducted for diverse orientations, the R-values of the envelope components were held to be the same as the base case condition.

The computer simulations for performance tests were conducted using two ANN-based logic approaches and two non-ANN-based counterparts. Simulations were conducted for limited periods of summer and winter in 2009, from 3 July to 8 July and from 27 January to 1 February, respectively.

Results and Discussion

Validation of simulation against measurement

Predicted simulation data were validated against measured data in the mock-up chamber in order to demonstrate reliability for further computer simulations of the residential buildings. The validation was performed using a linear regression method. The measured temperature in the chamber was the independent variable and the simulated temperature was the dependent variable. The linear prediction model proving the relationship according to ANOVA is summarised in Table 3.

The prediction model indicates that there is a significant relationship between the measured and simulated temperatures. The coefficient of determination was 0.8399 for the relationship. This implies that the error variance could be reduced by 83.99% when the simulated temperature was predicted based on the measured temperature in the chamber. The ANOVA test result shown in Table 3 demonstrates that the linear relationship between the measured and simulated temperatures was acceptable at a very low significance level.

Figure 8 shows an example of the difference between measured and simulated temperature for some selected cases that were used for the linear regression. Overall, the majority of differences did not exceed ± 1.0 K, and

Table 2. Building conditions and control logic for simulations.

Conditions & Logic		Base case	Alternative case
Insulation (m^2 K/W)	Roof	6.69	3.52, 7.04, 10.57, 12.33, 14.09
	Wall	3.35	1.76, 5.28, 8.81
	Window	0.61	0.35, 0.70, 1.06, 1.23, 1.41, 1.76
	Floor	3.7	–
	Door	0.2	–
Building Orientation		S	N, N-E, E, S-E, S-W, W, N-W
Control Logic		ANN-based temperature and humidity control	
		ANN-based PMV control	
		Non-ANN-based temperature and humidity control	
		Non-ANN-based PMV control	

Table 3. ANOVA result for linear relationship between measured and simulated temperature.

	Unstandardised coefficients			
Factors	B	Std. Error	t	Sig.
(Constant)	4.4648	0.43	10.44	0.00
Measured temperature	0.7928	0.02	39.51	0.00
ANOVA	$r^2 = 0.8399$, $F(1,298) = 1560.96$, Sig. = 0.00			

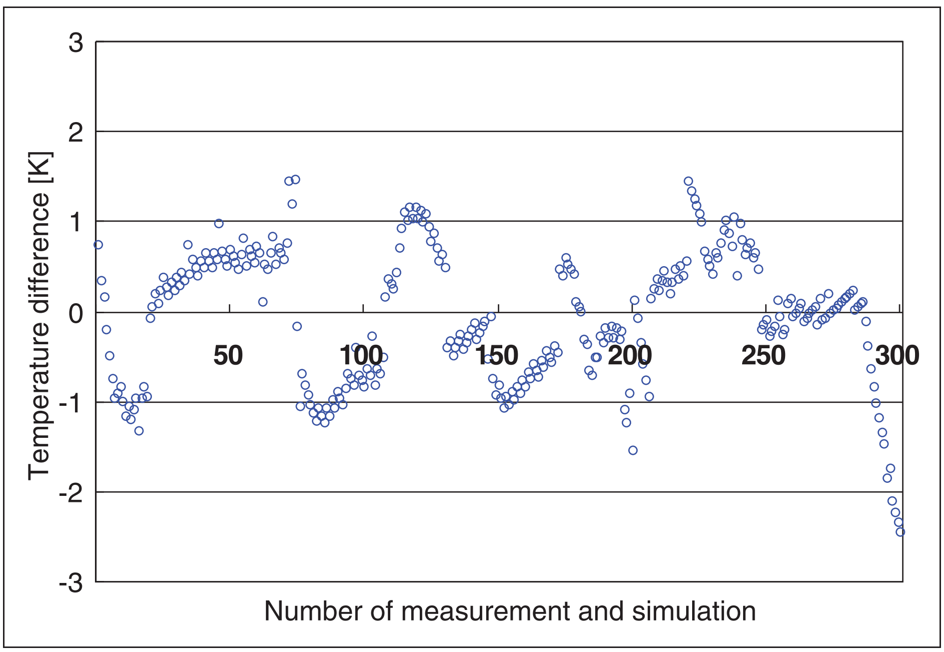

Figure 8. Difference of the measured and the simulated temperature.

the maximum difference between the measured and simulated temperature was −2.47 K. The narrow difference range was an effective contributor to the strong linear relationship between measured and simulated temperature, which was used for validation in this study.

These results imply that there is no significant difference between the measured and simulated temperature. In summary, this means that the validation of the simulated result against the measurement result was acceptable with strong reliability, and further computer simulations that are used to examine the effect of thermal control logic to the indoor environment of residential buildings also provide strong reliability.

Thermal performance of the ANN-based control logic

Performance analysis of the residential buildings in this study was conducted for two categories. The first category was the prediction accuracy of the developed ANN model and the second was thermal conditions for ANN-based and non-ANN-based logic in terms of thermal profiles, comfortable periods, and overshoots and undershoots.

Prediction accuracy of the ANN model

The prediction accuracy of the ANN model for the base case was examined based on comparison between the ANN-predicted $TEMP_{PRE}$ and the simulated $TEMP_{PRE}$ when the ANN-based temperature and humidity control logic were applied. The ANN-based $TEMP_{PRE}$ refers to the predicted value from the developed ANN model, and the simulated $TEMP_{PRE}$ is a numerically calculated value based on the MATLAB-IBPT simulation.

As shown in Figure 9, the maximum difference between the ANN prediction and the numerical simulation did not exceed ±0.5 K for all predictions performed in this study. The difference fell into a stable range with minimum and maximum differences of −0.4189 K and 0.4862 K, respectively.

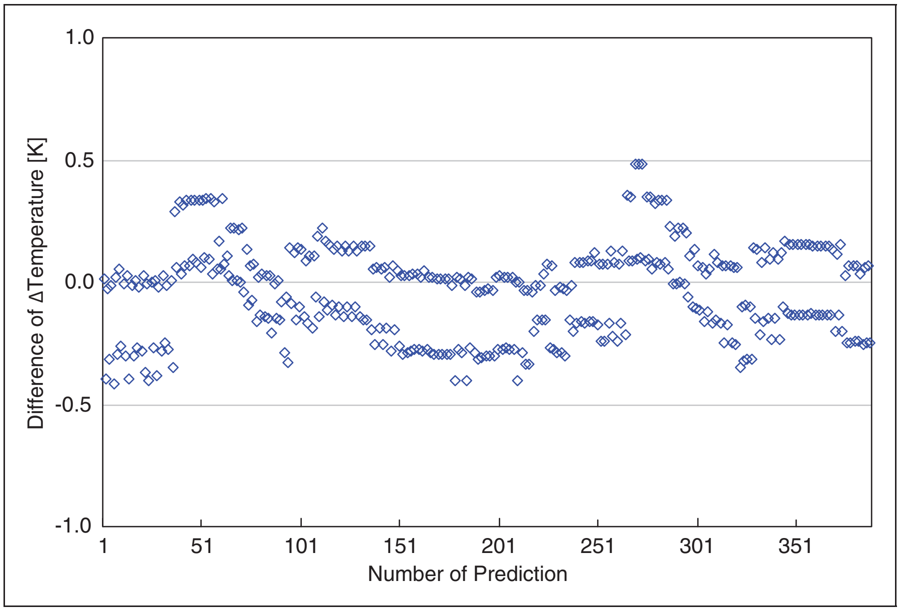

Figure 9. Difference of $TEMP_{PRE}$ between the ANN model and the computer simulation.

Table 4. ANOVA result for ΔTemperature between computer simulation and ANN based-logic.

	Unstandardised Coefficients			
Factors	B	Std. Error	t	Sig.
(Constant)	0.0071	0.00	3.06	0.00
Simulated temperature	0.3241	0.01	37.46	0.00
ANOVA	$r^2 = 0.7843$, $F(1, 386) = 1403.58$, Sig. = 0.00			

A linear regression model was developed for ANN-based predicted temperature and simulated temperature. Simulated temperature was the independent variable and temperature predicted by the ANN model was the dependent variable. ANOVA results between these variables are summarised in Table 4.

Overall, a fairly strong linear relationship existed between the temperature in the ANN-based model and the temperature in the computer simulation. The coefficient of determination (r^2) of the relationship was 0.7843. This implies that the error variance in $TEMP_{PRE}$ could be reduced by 78.43% when $TEMP_{PRE}$ in the numerical simulation was used to predict $TEMP_{PRE}$ in the ANN model.

The test results indicated that the linear relationship between the temperature in the ANN-based model and the computer simulation was acceptable at a significant level. In summary, the developed ANN model accurately predicted the indoor air temperature condition, since no significant difference existed between the temperatures from the two computation methods.

Profile of thermal factors

The variation in air temperature, humidity and PMV with ANN-based logic and non-ANN-based logic was calculated for the base case condition in order to compare the influence of control logic on the indoor thermal environment. The variations for a particular time period of a selected winter day are shown in Figure 10.

Overall, non-ANN-based temperature control logic caused wide fluctuations in temperature over a long time range, as shown in Figure 10(a). During this time period, the temperature ranged from 19.8 to 23.1°C whenever the heating system was turned on and off. The pattern of variation in temperature was stable, but the temperature deviated from a comfortable range for some time periods.

Although the non-ANN-based control did not always maintain a comfortable temperature, the ANN-based control logic kept the indoor temperature more stable, with a temperature range from 20.8 to

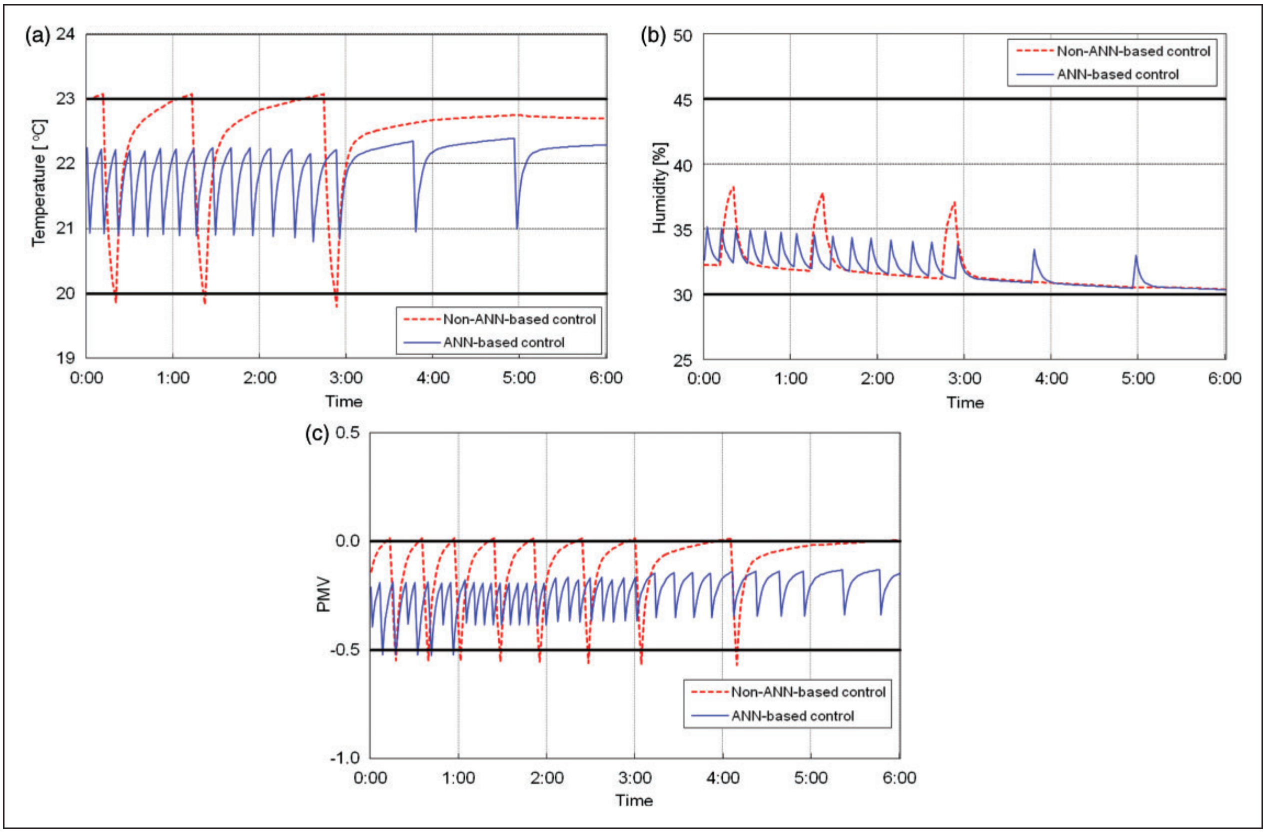

Figure 10. Comparative profiles of thermal factors of non-ANN and ANN-based logics in winter (Base case condition, 00:00–06:00, January 30, 2009) (a) Temperature control logic, (b) humidity control logic and (c) PMV control logic.

22.4°C during the entire time period. The time range for the fluctuation of the ANN-based control logic was shorter than that of the non-ANN-based logic. Therefore, ANN-based logic effectively maintained the targeted comfortable temperature range (20–23°C) selected in this study.

The variation in humidity for ANN-based and non-ANN-based control is shown in Figure 10(b). Similar to the variation in temperature, non-ANN-based logic caused a wide range of humidity with a long time interval; the humidity varied from 30.3% to 38.2% during the study period. The fluctuation in humidity with ANN-based logic was frequent, but the fluctuation range was within 3% for the entire time period. The fluctuation in humidity was caused by temperature movement. Since the humidity is inversely proportional to the temperature, when the temperature decreased the humidity increased and vice versa.

Similar to the temperature variation, PMV was conditioned more properly by the ANN-based PMV control logic, as shown in Figure 10(c). The ANN-based logic caused narrower fluctuation ranges than the non-ANN-based logic.

Comfortable periods

The thermal comfort period maintained by the ANN-based and non-ANN-based control logics was examined in order to analyse the thermal performance of the logics in buildings. The comfort period was calculated in terms of temperature, humidity and PMV when the two types of logic were employed under a variety of building envelope conditions and orientations in summer and winter. The comfortable periods for all conditions were expressed as a percentage.

Table 5 summarises the percentage of time within the comfortable range according to the R-values of the walls, roof and windows. With changes in the R-values of the walls, roof and windows, the ANN-based temperature and humidity control logic conditioned the indoor air temperature and humidity to be more comfortable than the non-ANN counterpart. In most cases, the comfortable periods were increased when ANN-based logic was applied. The increase reached 5.0% for temperature and 12.3% for humidity when the R-value of window was 1.76 m^2 K/W in winter.

However, in two unique cases (when the R-value of the walls was 5.28 m^2 K/W in summer and the R-value

Table 5. Percentage of period within comfortable range according to R-values (unit: %).

		Temperature				Humidity			
		Winter		Summer		Winter		Summer	
Building Envelope	R-value (m^2 K/W)	non-ANN	ANN	non-ANN	ANN	non-ANN	ANN	non-ANN	ANN
Wall	1.76	82.8	85.3	96.6	99.7	99.9	100	99.2	100
	3.35	95.8	100	96.1	100	99.9	100	99.2	99.9
	5.28	95.4	100	95.9	100	100	100	99.4	99.1
	8.81	95.3	100	96.0	100	100	100	99.5	100
Roof	3.52	90.5	94.1	96.3	100	99.9	99.8	99.2	100
	6.69	95.8	100	96.1	100	99.9	100	99.2	99.9
	7.04	96.0	100	96.1	99.9	100	100	99.2	99.5
	10.57	95.9	100	96.1	100	100	100	99.4	99.8
	12.33	95.9	100	96.1	100	100	100	99.4	99.5
	14.09	95.9	100	96.1	100	100	100	99.5	99.5
Window	0.35	84.7	87.52	96.17	100	80.35	88.04	72.38	79.74
	0.61	95.8	100	96.08	100	89.50	98.49	75.13	79.03
	0.70	95.78	99.96	96.06	100	88.89	97.03	75.82	82.27
	1.06	95.31	100	95.95	100	87.92	98.90	77.75	78.85
	1.23	95.20	100	96.00	99.97	87.72	97.32	78.36	85.09
	1.41	95.08	100	95.92	100	87.65	98.35	78.78	85.24
	1.76	95.00	99.99	96.00	100	87.63	99.96	80.18	85.38

of the roof was 3.52 m^2 K/W in the winter) the comfortable humidity period decreased by 0.3% and 0.1%, respectively. The reason for this is the lack of training process for the ANN model. In the earlier testing period, when the training process was insufficient to adapt to the given environment, the ANN model was likely to be incorrect. In addition, the number of times that the humidifying and dehumidifying devices turned on and off was significantly lower than that of the heating and cooling devices. Thus, the iterative self-tuning process was conducted to a lesser extent. As a result, the ANN model did not adapt sufficiently to produce error-free outputs. However, the number of erroneous results deceased as the test proceeded.

Table 6 summarises the comfortable PMV periods in winter and summer. In this case, the orientation of the tested building was south, which was the base case condition in this study. Overall, the residence was comfortable more than 70% of the time even when the worst-case insulation was used for the building envelope. The comfortable period in winter was longer than that in summer. For both seasons, ANN-based control logic increased the comfortable period for all cases compared to the non-ANN-based logic.

In general, as the insulation of the building envelope was improved, the comfortable periods were more significantly increased by ANN-based logic. For example, the difference between ANN-based and non-ANN-based logic in winter varied from 7.6 to 12.3% when the R-value of the window was changed from 0.35 to 1.76 m^2 K/W. This result implies that the contribution of ANN-based logic was more effective when heat transfer through the building envelope was reduced.

The variation in periods of comfort for diverse building orientations is shown in Figure 11. In this case, the R-values of the building envelope were fixed to the base case conditions. Similar to the insulation cases, the influence of ANN-based logic on the comfort period was stronger in winter than in summer. For example, the ANN-based temperature controls increased the comfortable temperature period by 5.2% when the building faced north in winter. The improvement range of the comfortable temperature period was from 2.6% when the building faced northeast in winter, to 5.2% when the building faced north in winter.

Humidity and PMV conditions were also better controlled by ANN-based logic, with maximum improvements of 0.8% when the building faced east in summer and 11.1% when the building faced east in winter. One exceptional case occurred for humidity when the building faced southwest in summer; during this period, the comfortable period of humidity decreased by 0.03%.

In summary, the results of this analysis indicate two meaningful aspects. First, ANN-based predictive and adaptive control logic maintains temperature and humidity better within the targeted comfortable ranges than

Table 6. Percentage of period within the PMV comfortable range according to R-values (unit: %)

		Winter		Summer	
Building Envelope	R-value (m^2 K/W)	Non-ANN based	ANN based	Non-ANN based	ANN based
Wall	1.76	76.4	82.2	70.4	78.2
	3.35	89.5	98.5	75.1	79.0
	5.28	88.3	100.0	78.3	88.6
	8.81	87.9	97.4	81.7	83.2
Roof	3.52	84.6	93.9	72.2	79.5
	6.69	89.5	98.5	75.1	79
	7.04	89.5	99.5	75.1	79.5
	10.57	89.2	100	76	79.7
	14.09	89	100	76.1	82.1
Window ?	0.35	80.35	88.04	72.38	79.74
	0.61	89.50	98.49	75.13	79.03
	0.7	88.89	97.03	75.82	82.27
	1.06	87.92	98.90	77.75	78.85
	1.23	87.72	97.32	78.36	85.09
	1.41	87.65	98.35	78.78	85.24
	1.76	87.63	99.96	80.18	85.38

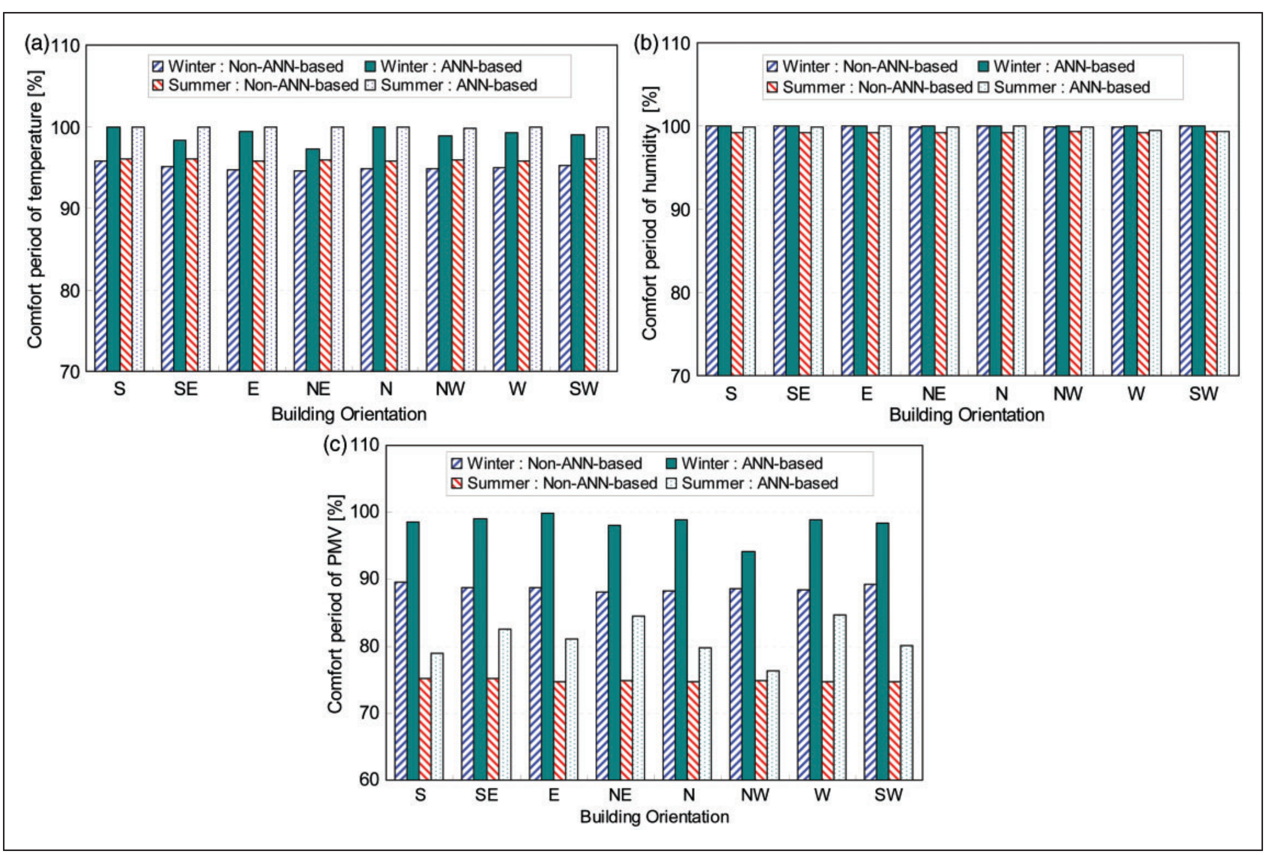

Figure 11. Comfort periods of temperature, humidity and PMV according to building orientation (R-value: base case condition). (a) Temperature control logic, (b) humidity control logic and (c) PMV control logic.

non-ANN-based controls. Second, the ANN models need to be sufficiently trained to reduce incorrect output.

Magnitudes of overshoots and undershoots

The magnitudes of overshoots and undershoots out of the targeted comfortable ranges were calculated and compared in order to examine the thermal control performance of the control logic. The magnitudes for each thermal factor were calculated using equation (4). The magnitude (S) refers to the summation of the multiplication of the degree (Δ) and the duration time (t_d). For example, the magnitude of temperature overshoots and undershoots was the duration time multiplied by the degree of overshoot or undershoot out of the targeted temperature comfortable range. The units of temperature, humidity and PMV magnitude are $K \times h$, $\% \times h$, and $PMV \times h$, respectively.

$$S = \sum(\Delta \times t_d) \tag{4}$$

The variation in the magnitude of overshoots and undershoots of temperature and humidity is shown in Figures 12 and 13. Overall, the ANN-based control logic stably maintained the thermal conditions within each targeted comfortable range. The magnitudes of temperature overshoot and undershoot were reduced with the change in R-value of the envelope (Figure 12). The amount of the reduction in temperature in winter ranged from 3.19 to 0.00785 $K \times h$ for overshoots and from 0.05433 to 0.10833 $K \times h$ for undershoots. Corresponding values in summer ranged from 0.0738 to 0.09100 $K \times h$ for overshoots and from 0.08000 to 0.12617 $K \times h$ for undershoots.

Similarly, in most cases the magnitude of humidity overshoots and undershoots was significantly reduced when the ANN control logic was employed in each season (Figure 13). The amount of magnitude reduction was determined to be from 0.00003 to 0.00317 $\% \times h$ for overshoots and from 0.00017 to 0.00567 $\% \times h$ for undershoots in winter, and from 0.09467 to 0.61667 $\% \times h$ for overshoots and from 0.00500 to 0.02450 $\% \times h$ for undershoots in summer.

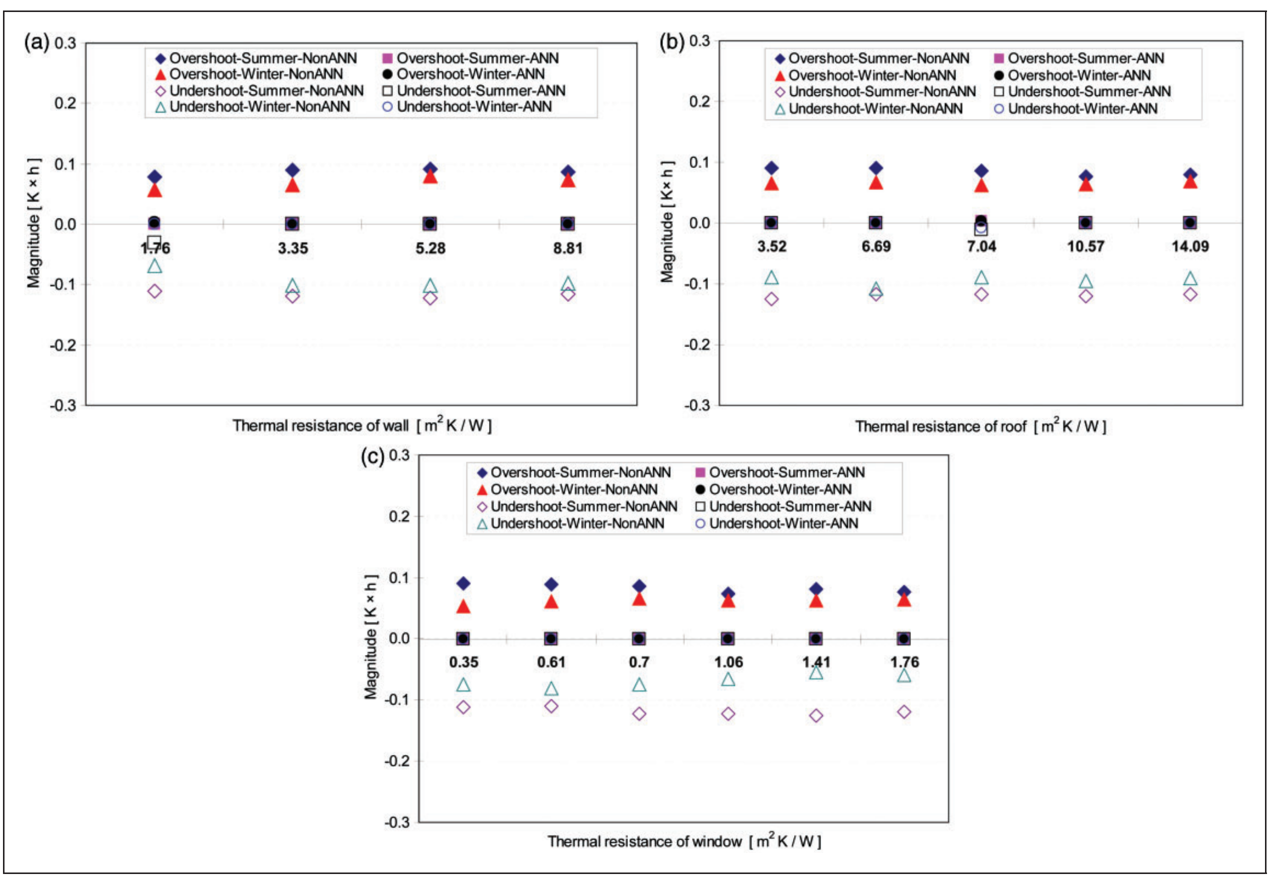

Figure 12. Magnitude of overshoots and undershoots of temperature according to the R-values of envelope components. (a) Magnitude variation according to R-value of wall, (b) magnitude variation according to R-value of roof and (c) magnitude variation according to R-value of window.

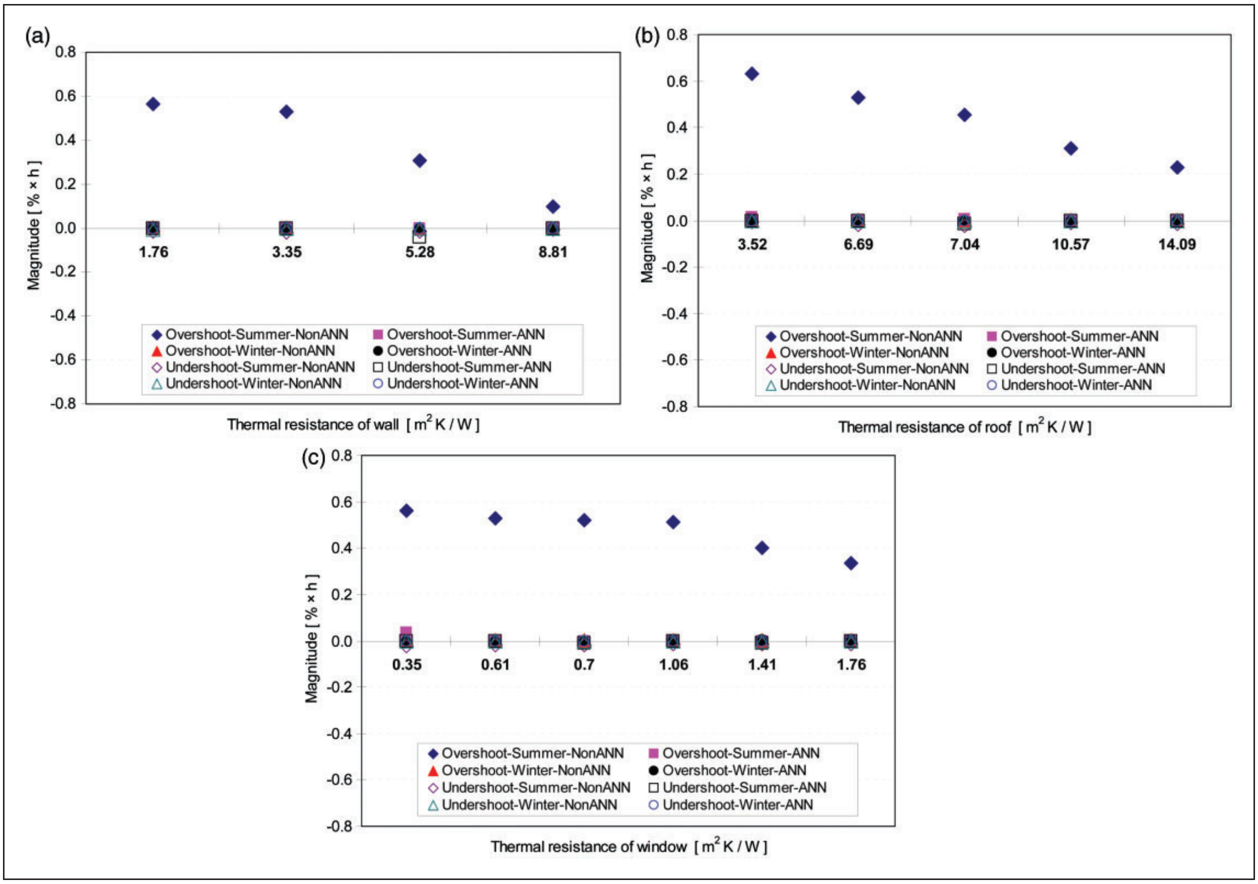

Figure 13. Magnitude of overshoots and undershoots of humidity according to the R-values of envelope components. (a) Magnitude variation according to R-value of wall, (b) magnitude variation according to R-value of roof and (c) magnitude variation according to R-value of window.

Several unique cases were observed for the humidity, four related to the change in window R-values and one related to the change in wall R-value. As described in the earlier section, these exceptions were due to deficiencies in the ANN training process. Before applying ANN to building thermal controls, proper training data are required and sufficient training must be conducted.

Similar to the temperature, the magnitudes of PMV overshoots and overshoots beyond the comfortable range were also effectively decreased by the ANN-based control logic, as shown in Figure 14. In winter, all of the magnitudes were reduced by applying ANN, which indicates that the thermal control performance of the ANN model was effective and met the targeted conditions. The ranges of the magnitude reduction for overshoots and undershoots were from 0.06450 to 0.11733 PMV $\times$ h and from 0.07800 to 0.14350 PMV $\times$ h, respectively, in winter, and from 0.10400 to 0.25417 PMV $\times$ h and from 0.141300 to 0.40483 PMV $\times$ h, respectively, in summer.

Based on analysis of the magnitude of reduction, the ANN-based temperature, humidity and PMV control logics demonstrated superiority for controlling target variables more stably within the comfortable ranges for the changes in envelope R-values.

For buildings with diverse orientations, the ANN-based control logic produced better results than its non-ANN-based counterpart in winter and summer, as shown in Table 7. In both seasons and in most cases, the magnitudes of temperature overshoot and undershoot for the different orientations were zero with ANN-based predictive and adaptive logic. In all cases, the magnitudes were decreased by ANN-based logic. Reductions in overshoots and undershoots ranged from 0.07183 to 0.07350 K $\times$ h and 0.09467 to 0.12067 K $\times$ h, respectively, in winter and from 0.04800 to 0.08917 K $\times$ h and 0.10983 to 0.15183 K $\times$ h, respectively, in summer.

Similar to the R-value changes of the building envelopes, unique cases occurred for the magnitude of humidity overshoots and undershoots in which the ANN-based humidity control logic produced greater overshoots and undershoots. This was also caused by a lack of a sufficient training process. However, in most cases the magnitudes were reduced when ANN-based logic was applied compared with non-ANN controls,

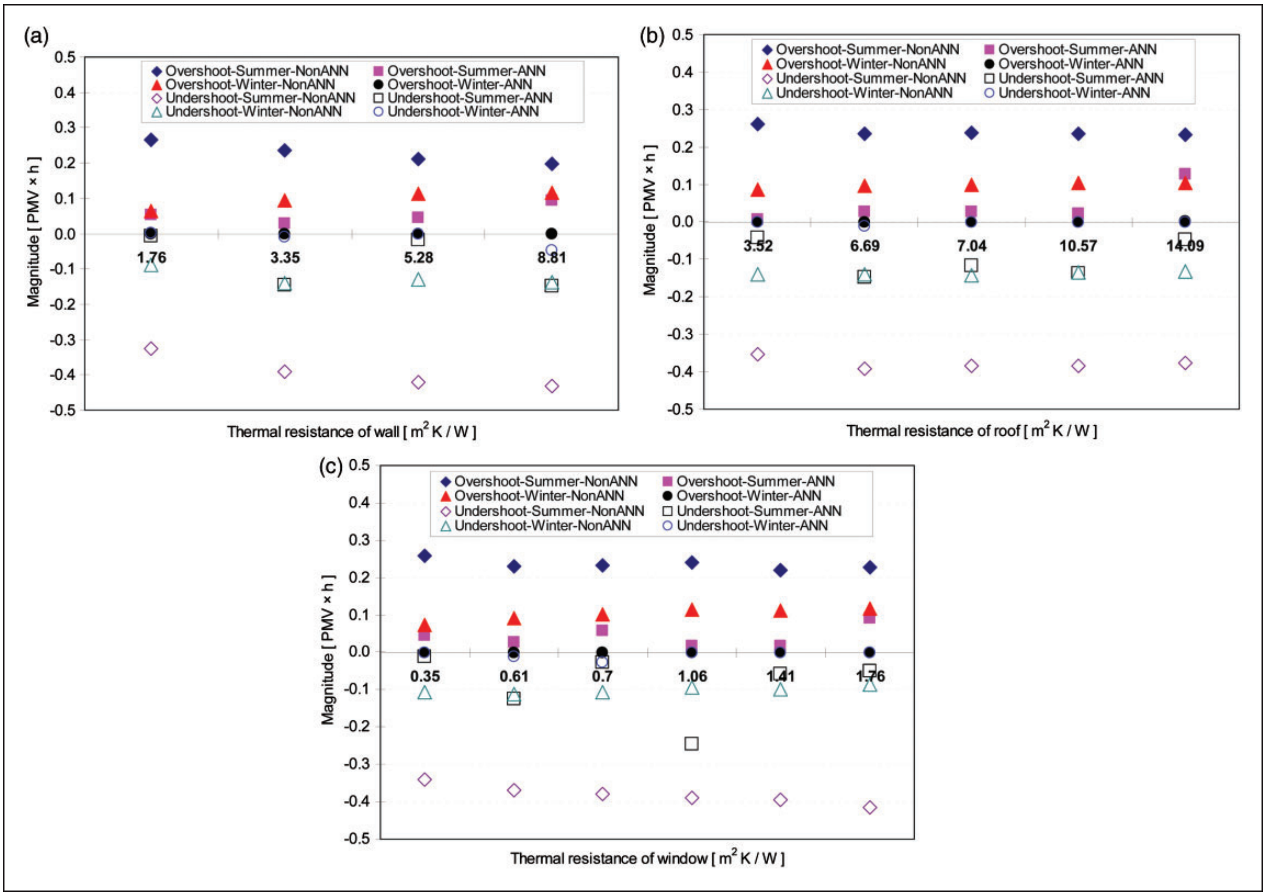

Figure 14. Magnitude of overshoots and undershoots of PMV according to the R-values of envelope components. (a) Magnitude variation according to R-value of wall, (b) magnitude variation according to R-value of roof and (c) magnitude variation according to R-value of window.

and the amount of reduction for overshoots and undershoots was up to 0.01150 % × h and 0.00183 % × h, respectively, in winter, and 0.08917 % × h and 0.15183 % × h, respectively, in summer.

The magnitudes of PMV overshoots and undershoots out of the targeted comfortable range were all reduced when the ANN model was applied in the control logic. The amount of reduction was from 0.07500 to 0.10567 PMV × h for overshoots and from 0.09400 to 0.18100 PMV × h for undershoots. Values for summer were more significant than those for winter, and ranged from 0.13183 to 0.21467 PMV × h for overshoots and from 0.16133 to 0.41650 PMV × h for undershoots.

Based on analysis of the magnitude of overshoots and undershoots of each thermal factor, the ANN-based control logic demonstrated superiority with regard to adaptation to changes in envelope insulation and building orientation. This improvement was due to the predictability and the adaptability of the developed ANN models.

Conclusions

This study proposes an ANN-based advanced thermal control method to effectively maintain indoor thermal environments. ANN models for predicting the future indoor temperature, humidity and PMV were developed and employed in the control logic. The performance of the developed control logic was compared with that of non-ANN counterparts. Numerical computer simulation was employed as the primary method for tests, and architectural variables such as diverse envelope insulation levels and building orientation were considered. A summary of the findings of this study is provided below.

1. The validity of the numerical simulation method was supported by the significantly high coefficient of determination for the regression model between measured and simulated values. The prediction accuracy of the ANN model was demonstrated by the statistical similarity between the ANN-predicted

Table 7. Magnitude of overshoots and undershoots of air temperature, humidity and PMV based on the orientation

		Winter		Winter		Summer		Summer	
		Non-ANN		ANN		Non-ANN		ANN	
Factor and unit	Orientation	Over shoot	Under shoot	Over shoot	Under shoot	Over shoot	Under shoot	Over shoot	Under shoot
Temperature (K × h)	S	0.06583	−0.10517	0.0	0.0	0.08917	−0.10983	0.0	0.0
	SE	0.06200	−0.10450	0.0	0.0	0.07433	−0.13967	0.0	0.0
	E	0.06833	−0.11300	0.0	0.0	0.07083	−0.14950	0.0	0.0
	NE	0.06533	−0.11633	0.0	0.0	0.06033	−0.14717	0.0	0.0
	N	0.07067	−0.12150	0.0	−0.00083	0.06733	−0.14567	0.0	0.0
	NW	0.06867	−0.11867	0.0	0.0	0.06617	−0.15183	0.01817	0.0
	W	0.07350	−0.11483	0.0	0.0	0.07633	−0.13900	0.0	0.0
	SW	0.06483	−0.09583	0.0	−0.00117	0.08900	−0.12667	0.0	0.0
Humidity (% × h)	S	0.00317	−0.00183	0.0	0.0	0.52783	−0.01833	0.00367	−0.00350
	SE	0.00083	−0.00133	0.0	−0.00067	0.48217	−0.01583	0.01167	−0.01383
	E	0.00033	−0.00017	0.0	0.0	0.52583	−0.00933	0.03733	0.0
	NE	0.01150	−0.00133	0.0	0.0	0.47083	−0.01050	0.0	−0.02417
	N	0.00117	−0.00100	0.00650	0.00033	0.49850	−0.01133	0.01950	0.0
	NW	0.00250	−0.00117	0.0	0.0	0.44400	−0.00767	0.00900	−0.02050
	W	0.00117	−0.00033	0.0	−0.00017	0.37533	−0.01650	0.01767	−0.05750
	SW	0.00017	−0.00017	0.00183	0.0	0.31567	−0.00767	0.0	−0.05350
PMV (PMV × h)	S	0.09633	−0.15183	0.0	−0.01167	0.23500	−0.39183	0.02750	−0.14683
	SE	0.08950	−0.15967	0.0	0.0	0.20867	−0.41767	0.00417	−0.00600
	E	0.09917	−0.17633	0.00200	0.0	0.16750	−0.43233	0.00017	−0.10217
	NE	0.09467	−0.18883	0.01967	−0.02333	0.14050	−0.44633	0.00100	−0.03467
	N	0.09550	−0.18400	0.0	−0.00300	0.15733	−0.45317	0.00017	−0.06950
	NW	0.09833	−0.18367	0.0	−0.08967	0.14600	−0.45667	0.01417	−0.29533
	W	0.10333	−0.17400	0.0	0.0	0.17383	−0.43283	0.00017	−0.01633
	SW	0.10567	−0.16017	0.0	0.0	0.21733	−0.41033	0.00267	−0.09950

values and the simulated values, for which the developed ANN models demonstrated applicability to the control logic.

2. The profile comparisons between ANN-based and non-ANN-based logic for temperature, humidity and PMV proved the superiority of the ANN-based logic. ANN-based logic properly conditioned each thermal factor within the targeted comfortable ranges, whereas non-ANN-based logic resulted in deviation from the comfortable ranges.
3. Comfortable periods for temperature, humidity and PMV increased in most cases for the architectural variables tested when the ANN-based control logic was applied. Some exceptions existed as a result of the lack of a sufficient training process for the ANN model. Sufficient model training is required before application to actual buildings in order to prevent erroneous outputs.
4. ANN-based logic demonstrated superiority in conditioning the thermal environment more stably with decreased magnitudes of overshoots and undershoots in temperature, humidity and PMV. Exceptions existed in limited cases, indicating that sufficient self-training of the models is necessary before their application.

In summary, ANN-based thermal control logic was able to maintain the indoor thermal environment more comfortably and stably within the targeted comfortable ranges than non-ANN control. This advancement reflects the predictive and adaptive features of ANN models, but these models need to be sufficiently trained before application.

In this study, the performance of the developed ANN-based control logic was tested primarily for a limited number of variables using a numerical computer simulation. Further studies are necessary for application of the developed logics to actual buildings and examination of their performance. Such studies should support the applicability of the developed control logics to various building-related conditions.

Authors' contributions

All authors participated in preparing the research from the beginning to ends, such as establishing research design, method and analysis. All authors discussed and finalised the analysis results to prepare manuscript according to the progress of research.

Declaration of conflicting interests

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