APPLICATION OF ANN (ARTIFICIAL-NEURAL-NETWORK) IN RESIDENTIAL THERMAL CONTROL

Jin Woo Moon, Sung Kwon Jung, and Jong-Jin Kim
TCAUP, University of Michigan, Ann Arbor, USA

ABSTRACT

This paper presents Artificial Neural Network (ANN)-based predictive and adaptive thermal control strategies for residential buildings designed to advance thermal comfort. For residential buildings, we developed a thermal control strategy framework, with four thermal control logics therein, including two predictive logics with ANN models incorporating the Neural Network (NN) toolbox in MATLAB. Using computer simulation with International Building Physics Toolbox (IBPT), a typical two-story single-family home in the U.S. was modelled for testing each logic's performance. Through analysis, we found that application of ANNs in thermal control of single-family homes has potential for enhancing thermal comfort with increased comfort period and reduced over and undershoots.

INTRODUCTION

Historically, application of thermal control systems to residential buildings has been simplistic. The thermostat has been the principal control system because, at least *prima facie*, homeowners did not see sophisticated control systems as economically worthwhile. However, such perceptions have changed. Increasing consciousness of quality of life has led homeowners to want thermal conditions in their homes conducive to improved comfort and health (Parsons, 2003). In addition, as energy costs increase significantly, home energy efficiency acquires economic importance. Simultaneously, the emergence of the home office concept has made productivity become an important economic factor (Harper, 2003). Accordingly, new residential buildings demand advanced climatic control strategies providing comfort, health, productivity and energy efficiency.

ANN application to thermal control in buildings

Artificial-Neural-Network (ANN) increasingly has been applied for advanced thermal control of buildings. Analogous to the human brain and its learning process, ANN utilizes connectivity and transfer functions between input, hidden, and output neurons, and successfully has been applied to non-linear systems or systems with unclear dynamics. In particular, different from mathematical models such as regression models or proportional-integral-derivative (PID) controllers, ANN models have adaptability through a self-tuning process, so can decide accurately without outside expert intervention when unusual perturbations, disturbances, and/or changes in building background conditions occur. Studies proved ANN-based predictive control strategy has advantages as a thermal control method over mathematical strategies in terms of the accurate thermal control with reduced overheating and overcooling, and the improved energy efficiency (Gouda et al., 2006, Ruano et al., 2006, Loveday, 1992).

ANN models were applied to determine optimal start and stop times for heating systems. These studies used the predicted values from ANN in the algorithms: the turning on time of the heating system for restoring the interior temperature to the comfortable level at the start of business hours; and the amount of time for interior temperature to drop down to the lower limit of comfort range. This predictive control improved thermal comfort and energy efficiency (Yeo et al., 2003, Yang et al., 2000). A similar study was conducted for optimal start of A/C systems employing ANN for predicting end-of-setback moment; in these, the ANN-based predictive control proved accurate and easy to use (Ben-Nakhi et al., 2002).

ANN application to hydronic heating of solar building by prediction of outdoor temperature, solar radiation, indoor temperature, and supply temperature showed significant energy savings (Argiriou et al., 2004). In addition, residential water heating systems and radiant floor heating systems were controlled effectively by predictive control methods (Morel et al., 2001, Lee et al., 2002). As a more advanced method, ANN was used to control a radiant heating device in conjuction with Fuzzy logics. The predicted indoor air temperature by ANN and its difference from the setpoint temperature were used as inputs for the Fuzzy controller. Reduction of overshoots and energy consumption was remarkable compared to the PI control (Gouda et al., 2006). Studies on the ANN application to cooling systems were conducted also. The adaptive model with sliding window data sets proved more effective in controlling cooling systems with better temperature regulation and energy saving than did the fixed model or state-of-the-art physical models (Ruano et al., 2006).

Limitations of Existing ANN Models

To date, in most residential buildings, optimization of thermal comfort and energy consumption is not achieved. The currently-widespread thermal control method, thermostat-dependent, creates thermal discomfort due to time-lag of heating or cooling equipment and late thermal response of the space. Recently developed predictive control strategies with ANN have improved this undesirable situation by creating comfortable air temperature condition.

Previous studies, however, regarded indoor air temperature as the only control variable, while other important thermal factors such as humidity and PMV rarely were considered. Therefore, it is beneficial to develop control strategies that are capable of regulating building thermal systems based on factors consisting of thermal comfort including humidity and PMV. At the same time, the control strategies with ANN models need to test their perfornance and adaptability for a change of environmental requirements (e.g., application of setback), which may cause inaccuracy in an ANN prediction.

Objectives

This study aimed to develop an advanced residential thermal control strategy. In order to achieve this objective,

1. ANN-based predictive thermal control methods are developed, which control overall thermal conditions including not only air temperature, but also humidity or PMV. In particular, PMV is calculated using six parameters: air temperature, humidity, mean radiant temperature (MRT), air velocity, metabolic rate (MET), and clothing level (CLO).
2. The adaptability of predictive methods is tested by application of two cases: non-application of setback and application of setback.
3. The energy efficiency of ANN-based predicitive control strategies is comparatively investigated with non-predictive strategies.

To this end, a framework of control logic, with five steps therein, were developed.

DEVELOPMENT OF CONTROL LOGIC

In the development phase of control logic, an overall framework of control logic and four component control logics were developed using MATLAB and its Neural Network (NN) toolbox. Figure 1 shows the control logic framework. In Step one, climatic conditions and personal conditions transfer to the control panel. Sensors and user input are required in this step. In Step two, thermal comfort range, users set system operating ranges, or the logic recommends them for proper home climate control devices such as heating, cooling, humidifying and dehumidifying systems. In Step three, energy, users decide on a setback value and a period. Or the control system recommends them to reduce energy consumption. In Step four, decision of system operation, the control algorithm decides the operation of environmental control devices. Previously acquired information, such as current and past climatic conditions, personal conditions, operating range, and setback is utilized in this step. In particular, ANN models were applied in the logic to predict future thermal conditions of air temperature, humidity, and PMV. In Step five, operation of control devices, the control devices such as heating, cooling, humidifying, and dehumidifying systems work for improving thermal conditions based on the signals decided in the previous control logic.

Four different thermal control logics were employed in system operation decision: (1) temperature and humidity control without ANNs as with conventional strategy, (2) temperature and humidity control with ANNs, (3) PMV control without ANN, and (4) PMV control with ANN. The last three logics are regarded as alternative new control logics. Among these, two predictive control logics with ANN models (2 and 4) employed the predicted future indoor air temperature, humidity, or PMV values in the algorithms.

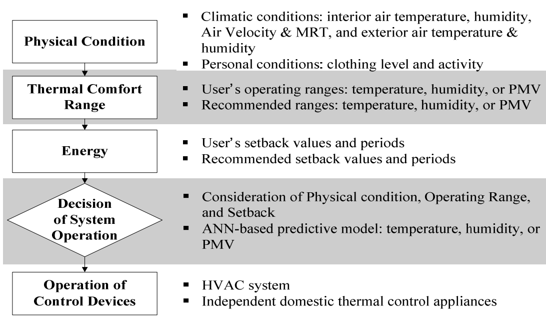

Figure 1 Framework of the thermal control logic

Air temperature profiles of a conventional logic and a predictive logic are compared conceptually in Figure 2. While the conventional logic creates overshoot and undershoot by a time lag between the operation of environmental control devices (a heater for instance) and building response, the predictive logic better stabilizes air temperature within the designated range because it predictively operates heating and cooling devices before room air temperature reaches designated boundary conditions. Such early decision is possible by the predictive nature of ANN models. A maximum amount of temperature rise or drop is predictively determined when the current operating mode of control device is changed. For example, in the heating season, ∆Temperature is the maximum rise of temperature after stopping the currently working heating device (Yang et al., 2003).

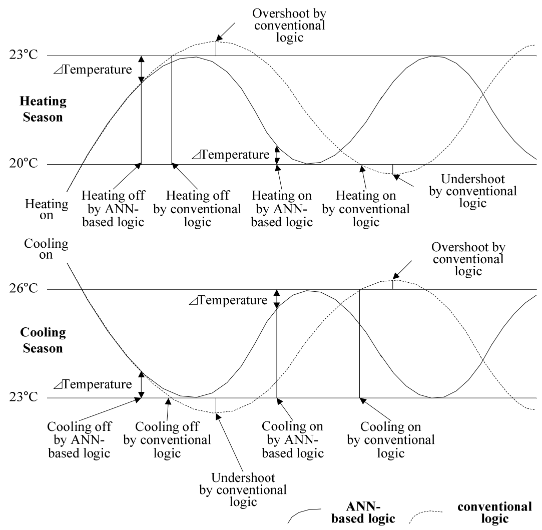

Figure 2 Comparison of air temperature profile between a conventional and a predictive logic

Figure 3 shows the structure of ANN models for predicting air temperature, humidity, and PMV. Three identical feed-forward and back-propagation ANN models were applied. Eight-input neurons were assigned to the input layer: i) exterior air temperature, ii) exterior air temperature change from the preceding hour, iii) exterior humidity, iv) exterior humidity change from the preceding hour, v) interior air temperature, vi) interior air temperature change from the preceding ten minutes, vii) interior humidity, and viii) interior humidity change from the preceding ten minutes.

Since there is not a fixed scientific solution for the design of optimal ANN model, this study employed the empirical solutions used in the previous studies for ANN model design. One layer was used for the hidden layer, thus total three layers consisted of the ANN model including one input and one output layer. Seventeen neurons were used in a hidden layer based on Equation 1 (Yang et al., 2005, Datta et al., 2000). Output of each ANN model was generated at every minute for ΔTemperature, ΔHumidity, and ΔPMV, respectively. One hundred and sixty training data sets were prepared for each model based on the Equation 2 (Kalogirou et al., 2000). Training data sets were collected from a pre-simulation which used non-application of setback as variable for first five days of 2007. ANN models adopted a sliding window method, so the new data set at the system on/off moment was added to the training data sets, replacing the oldest.

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

$N_d = (N_h - 1/2 \times (N_i + N_o))^2$ (Equation 2)

Where,

N_i: number of input neurons

N_h: number of hidden neurons

N_o: number of output neurons

N_d: number of data sets

Based on previous research conducted by Yang et al. for predicting thermal conditions in the building, training goals (MSE (mean square error)) for air temperature was set to 0.1°C, humidity to 0.1% and PMV to 0.1 with maximum 1,000 times epoch, 0.75 learning rate, and 0.9 momentum (Yang et al., 2003). In addition, Levenberg-Marquardt algorithm was used as a training method considering training speed and accuracy (Mathwork, 2005).

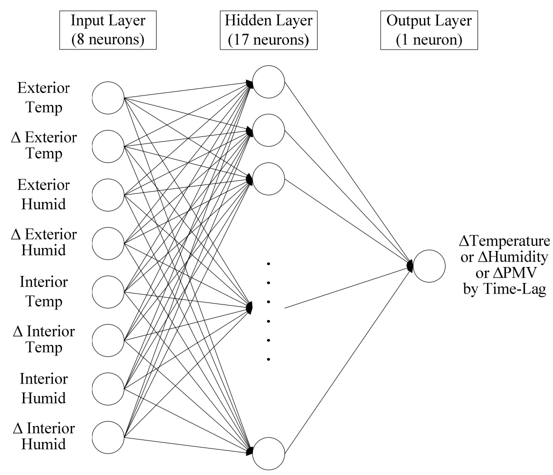

Figure 3 Structure of ANN models

SIMULATION

The performance of developed control logics was tested through computer simulation. Using computer simulation, identical climatic conditions such as exterior air temperature and humidity could be applied to each simulation run. In addition, tests for diverse cases such as application of setback could be easily conducted. For the simulation, two major means were incorporated: International Building Physics Toolbox (IBPT) and MATLAB. The IBPT was used for (1) modelling building components and related features (e.g., envelopes, control devices, ventilation rate, internal load, initial thermal conditions, and import of weather data), and (2) calculating interior thermal conditions: air temperature and humidity. Using these calculated air temperature and humidity values, MATLAB was utilized for (1) calculating interior PMV, (2) predicting air temperature, humidity, and PMV using ANN models, and (3) deciding operation of control devices based on current and predicted values. This decision was fed into the IBPT for system operation, and new interior thermal conditions as a result of system working were used in MATLAB iteratively (IBPT, 2008, MathWorks, 2005).

Target building

Based on the American Housing Survey (U.S. Census Bureau, 2005), a typical two-story detached residential house was modelled as a test building with 184.4 m^2 (≈2,000 ft^2) area. Envelopes consist of R3.346 (R19 U.S.) walls, R6.692 (R38 U.S.)

roof, R3.698 (R21 U.S.) floor, R0.606 (R3.44 U.S.) windows, and R0.215 (R1.22 U.S.) doors. Surface heat transfer coefficient was taken into account, also. The window wall ratio (WWR) was 0.15 on average (0.24 for south, 0.08 for north, 0.14 for east, 0.13 for west) (Figure 4).

Hourly-weighted heat and moisture gains for a family of four people were considered as internal load (ASHRAE, 2004, McArthur et al., 2004). A ventilation rate of 0.3 ACH was assumed constantly. Initial interior thermal conditions were 23°C for air temperature and 45% for humidity. In addition, it was assumed that MRT of space was the same as air temperature, air velocity was 0.0m/s, activity level was 1.0MET, and clothing level was 1.0 and 0.5CLO for winter and summer, respectively.

Convective heating (9,000 Watt heat supply) and cooling (10,000 Watt heat removal) as well as humidifying (1.41 Kg/hr moisture supply) and dehumidifying (2.36 Kg/hr moisture removal) devices were equipped for controlling thermal conditions. TMY2 data for Detroit, Michigan, were used as weather data.

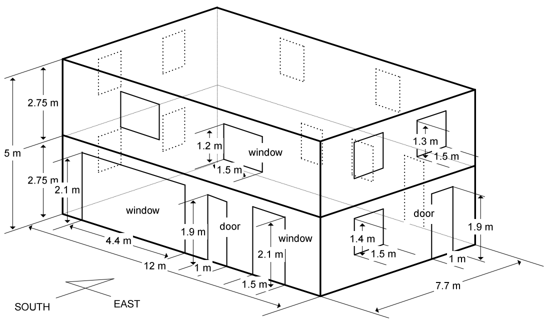

Figure 4 View of a target building

Schedule and variables

Control logic was tested for two seasons: winter and summer. Six days were simulated for each season: Jan. 27~Feb. 01, 2007 for winter; July. 03~08, 2007 for summer. Each period represented peak days of heating and cooling. Analysis was conducted for the last five days after trimming away the first day.

Control logic was tested for two cases: non-application and application of setback. Non-application of setback specified comfort ranges for temperature, humidity and PMV as below:

- Air Temperature: 20~23°C for heating, 23~26°C for cooling
- Humidity: 30~45% for humidifying, 45~60% for dehumidifying
- PMV: -0.5~0.0 for PMV increasing, 0.0~0.5 for PMV decreasing

Application of setback employed day- and night-time setback modes. Figure 5 shows the application of setback modes for a day.

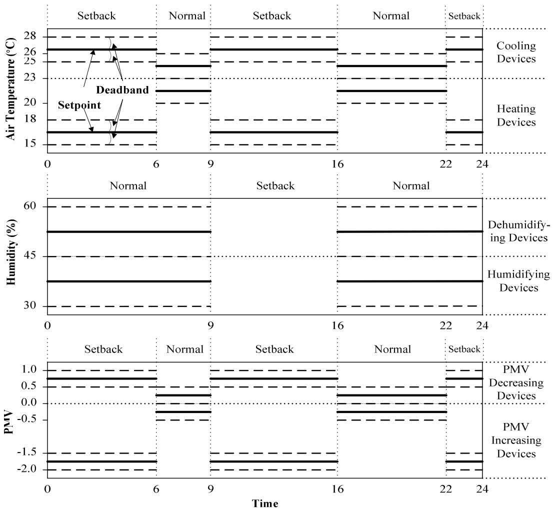

Figure 5 Application of setback

DISCUSSION AND RESULT ANALYSIS

Simulation results were analyzed for the percentage of periods within specified ranges; magnitude of overshoots and undershoots out of specified range; and energy consumption.

Percentage of periods within specified ranges

The percentages of periods when indoor conditions (air temperature, humidity or PMV) are within specified ranges were calculated.

1. Non-application of setback

Control logic with ANN models created the more comfortable thermal conditions (Table 1). Compared to the conventional logic, i.e. temperature and humidity control without ANNs, using temperature and humidity control with ANNs, the percentage of period when air temperature is within specified ranges increased 4.2% in winter and 3.9% in summer; and humidity control improved 0.1% in winter and 0.7% in summer . Periods when PMV is within the specified ranges improved by 9.0% in winter and by 3.9% in summer using PMV control with ANN as compared to PMV control without ANN. These improvements using the predictive logic were due to the reductions of overshoot and undershoot out of specified range. In addition, control logic having PMV as a control variable had a higher PMV comfort period. This indicates the potentials of the PMV-based control method in improving thermal comfort in residential buildings.

2. Application of setback

When day- and night-time setback modes were applied, ANN-based predictive controls improved thermal comfort (Table 2). Period when air temperature is within the specified ranges increased by 2.6% in both seasons. In specific, using the temperature and humidity control with ANNs, percentages of period in normal period (20~23°C) and setback period (15~18°C) in winter, and in normal period (23~26°C) and setback period (25~28°C) in summer were improved by 3.1, 2.4, 5.0, and 1.1%, respectively. In addition, period when humidity is within the specified ranges increased by 0.8% in winter and 2.6% in summer. By PMV control with ANN, period when PMV is within the specified ranges improved 6.8% in winter and 6.4% in summer. Each percentage in normal period (-0.5~0.0) and setback period (-2.0~-1.5) in winter, and in normal period (0.0~0.5) and setback period (0.5~1.0) in summer were improved by 6.4, 7.0, 14.9, and 1.1%, respectively.

Based on comparisons of percentage of periods for non-application and application of setback, it can be concluded that the predictive control logics with ANN would control indoor thermal conditions better within the user specified ranges, and, thus, would make occupants feel more comfortable.

Magnitude of overshoots and undershoots out of specified ranges

The magnitude of a control system overshoots or undershoots can be measured by a combination of two factors: the duration time (t) and the degree (Δ) of overshoots or undershoots. The multification of these two factors (Δ × t) will indicate the magnitude of over- or under-shoots as in Equation 3. Figure 6 exemplifies it for overshoot of air temperature using the shadowed area. The magnitude of shoots out of specified range by each control logic was compared for air temperature, humidity, and PMV. Units were °C×minutes, %×minutes, and PMV×minutes, respectively.

$$S = \sum(\Delta \times t) \qquad \text{(Equation 3)}$$

Where,

S = magnitude of over or undershoots

Δ = degree of over or undershoots out of specified range

t = duration time of over or undershoots

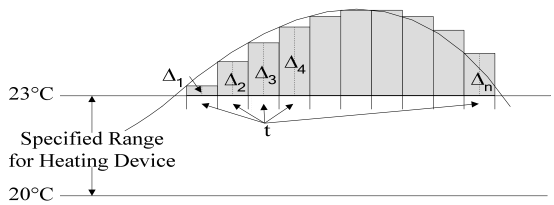

Figure 6 Magnitude of Overshoot of Air Temperature

Table 1
Percentage of Periods (%) within Specified Ranges: non-application of setback

SEASON	SPECIFIED RANGES	TEMP/HUMID CONTROL W/O ANNS	TEMP/HUMID CONTROL WITH ANNS	PMV CONTROL W/O ANN	PMV CONTROL WITH ANN
Winter	Air Temperature (20~23˚C)	95.8	100.0	73.8	99.9
	Humidity (30~45%)	99.9	100.0	0.4	0.0
	PMV (-0.5~0.0)	53.5	42.9	89.5	98.5
Summer	Air Temperature (23~26˚C)	96.1	100.0	32.2	38.8
	Humidity (45~60%)	99.2	99.9	61.2	48.7
	PMV (0.0~0.5)	4.8	0.0	75.1	79.0

Table 2
Percentage of Periods (%) within Specified Ranges: application of setback

SEASON	SPECIFIED RANGES		TEMP/HUMID CONTROL W/O ANNS	TEMP/HUMID CONTROL WITH ANNS	PMV CONTROL W/O ANN	PMV CONTROL WITH ANN
Winter	Air Temperature	15~18 (°C)	75.0	77.4	75.7	76.6
		20~23 (°C)	70.9	74.0	66.9	78.9
		Overall	73.5	76.1	72.4	77.5
	Humidity	30~45 (%)	98.5	99.3	0.0	0.0
	PMV	-2.0~-1.5	54.3	66.8	64.2	71.2
		-0.5~0.0	35.4	21.4	58.2	64.6
		Overall	47.2	49.8	61.9	68.7
Summer	Air Temperature	25~28 (°C)	77.3	78.4	81.2	94.6
		23~26 (°C)	94.7	99.7	28.8	25.8
		Overall	83.8	86.4	61.4	68.7
	Humidity	45~60 (%)	94.3	96.9	69.1	67.6
	PMV	0.5~1.0	18.7	5.6	53.3	54.4
		0.0~0.5	11.8	0.7	75.9	90.8
		Overall	16.1	3.8	61.9	68.3

1. Non-application of setback

The total over or undershoots of air temperature controlled by the ANN predictive logic were all zero, which means that air temperature always stayed within the specified ranges. On the other hand, summations of shoots by the logic without ANN showed a certain amount of over and undershoots of air temperature by heating and cooling operations. Similarly, summations of shoots of humidity were reduced significantly by the predictive logic. In addition, summations of shoots of PMV by the PMV control with ANN were less than that of a logic without (Table 3).

2. Application of setback

Similar to the cases with non-application of setback, the magnitudes of over or undershoots of air temperature and humidity were both reduced by the predictive logic. Likewise, those of PMV also decreased by the PMV control logic with ANN (Table 4).

Reduction of overshoots and undershoots by the predictive logic for non-application and application of setback indicates that a predictive logic with ANN models would maintain thermal conditions more stably within the user specified ranges. This has a thread of connection with the increased comfort period by the predictive logic.

Energy consumption

As a way of measuring energy consumption by climate control equipments controlled by different control logics, amounts of heat supply by a heater, heat removal by an air-conditioner, moisture supply by a humidifier, and moisture removal by a dehumidifier were calculated and compared for each control logic. The actual energy consumption by those climate control equipments can be determined by applying their energy efficiencies.

1. Non-application of setback

The predictive logic saved energy in most device operations. However, there were exceptional cases

Table 3
Summation of shoots out of specified ranges: non-application of setback

SEASON	SYSTEM OPERATIONS (UNIT OF SUMMATION)	TYPES OF SHOOTS	TEMP/HUMID CONTROL W/O ANNS	TEMP/HUMID CONTROL WITH ANNS	PMV CONTROL W/O ANN	PMV CONTROL WITH ANN
Winter	Heating (˚C×minutes)	Overshoots	3.96	0.00	-	-
		Undershoots	-6.10	0.00	-	-
	Humidifying (%×minutes)	Overshoots	0.19	0.00	-	-
		Undershoots	-0.11	0.00	-	-
	PMV increasing (PMV×minutes)	Overshoots	-	-	5.78	0.00
		Undershoots	-	-	-9.11	-0.65
Summer	Cooling (˚C×minutes)	Overshoots	5.41	0.00	-	-
		Undershoots	-7.07	0.00	-	-
	Dehumidifying (%×minutes)	Overshoots	31.67	0.22	-	-
		Undershoots	-1.10	-0.21	-	-
	PMV decreasing (PMV×minutes)	Overshoots	-	-	14.10	1.65
		Undershoots	-	-	-23.51	-8.81

Table 4
Summation of shoots out of specified ranges: application of setback

SEASON	SYSTEM OPERATIONS (UNIT OF SUMMATION)	TYPES OF SHOOTS	TEMP/HUMID CONTROL W/O ANNS	TEMP/HUMID CONTROL WITH ANNS	PMV CONTROL W/O ANN	PMV CONTROL WITH ANN
Winter	Heating (˚C×minutes)	Overshoots	1.89	0.00	-	-
		Undershoots	-7.35	-6.66	-	-
	Humidifying (%×minutes)	Overshoots	-	-	-	-
		Undershoots	-	-	-	-
	PMV increasing (PMV×minutes)	Overshoots	-	-	3.98	2.51
		Undershoots	-	-	-7.54	-0.46
Summer	Cooling (˚C×minutes)	Overshoots	5.31	0.00	-	-
		Undershoots	-7.67	0.00	-	-
	Dehumidifying (%×minutes)	Overshoots	49.46	1.79	-	-
		Undershoots	-0.04	0.00	-	-
	PMV decreasing (PMV×minutes)	Overshoots	-	-	12.95	1.11
		Undershoots	-	-	-24.82	-9.02

such as humidifying in winter and cooling in summer by the temperature and humidity control with ANN. In these cases, 3.0% more moisture was supplied and 0.1% more heat was removed compared to the logic without ANN. It indicates that the energy efficiency using predictive control method would not improve for the control devices having less time-lag such as humidifier and air-conditioner. In other cases, control logic with ANN models saved from 0.3% for cooling and dehumidifying (for PMV decreasing) by the PMV control with ANN in summer to 2.5% for dehumidifying by the temperature and humidity control with ANN in summer (Table 5).

2. Application of setback

The predictive logic reduced the amount of device operation in both seasons (Table 6). The amount of reduction ranged from 0.4% for cooling and dehumidifying (for PMV decreasing) by the PMV control with ANN in summer to 2.4% for dehumidifying by the temperature and humidity control with ANN in summer.

The PMV-based control logics consumed more energy in winter while less energy in summer compared to the temperature- and humidity-based control logics. The increase in winter was due to the higher specified range for PMV than those for temperature and humidity. Thus, PMV control logics consumed more heating and humidifying energy than temperature and humidity control logics. On the contrary, PMV control logics consumed less cooling and dehumidifying energy compared to the temperature and humidity control logics in summer. This is also due to the higher specified range for PMV in summer, therefore, less cooling and dehumidifying were required by PMV control logics.

Based on the analysis of the amount of device operations for non-application and application of setback, it is concluded that generally some savings of energy would result via predictive control logic; however, its amount was not as significant as expected. This was due to the time compensation between operating and non-operating time. For example, in a cycle, operating time of a heating device by the predictive logic is shorter than that of the non-predictive logic because the predictive logic turned off a device earlier than the non-predictive logic. And, non-operating time is also shorter by the predictive logic. Thus, the frequency of device's on and off was higher by the predictive logic. Therefore, the amount of energy consumption by the predictive logic, which decreased by the shorter operating time but increased by the higher frequency of device's on and off, showed similar results with that of the non-predictive logic.

CONCLUSIONS

This study aimed at developing advanced thermal control strategies for residential buildings. A framework for incorporating ANN in home climatic control was developed. Four control logics, which included one conventional and three proposed logics, were examined. Their performance test using computer simulation was conducted for two cases: non-application and application of setback. Findings from this study are:

1. ANN-based predictive control methods demonstrated that they could predict indoor temperature and humidity with a high accuracy, and that they were more advantageous in controlling home climate control devices in achieving user spcified conditions than conventional thermostat control.

Table 5
Amount of system operation: without of setback

SEASON	SYSTEM OPERATIONS	TEMP/HUMID CONTROL W/O ANNS	TEMP/HUMID CONTROL WITH ANNS	PMV CONTROL W/O ANN	PMV CONTROL WITH ANN
Winter	Heating (KWh)	691.2	684.8	702.8	693.2
	Humidifying (Kg)	13.3	13.7	110.1	108.6
Summer	Cooling (KWh)	287.3	287.7	255.0	254.3
	Dehumidifying (Kg)	151.4	147.6	60.2	60.0

Table 6
Amount of system operation: with setback

SEASON	SYSTEM OPERATIONS	TEMP/HUMID CONTROL W/O ANNS	TEMP/HUMID CONTROL WITH ANNS	PMV CONTROL W/O ANN	PMV CONTROL WITH ANN
Winter	Heating (KWh)	582.5	571.8	577.1	574.5
	Humidifying (Kg)	0.0	0.0	90.4	90.0
Summer	Cooling (KWh)	272.0	266.3	236.2	235.3
	Dehumidifying (Kg)	118.4	115.6	55.7	55.5

2. Control logic having PMV as the control variable showed an improved PMV comfort period compared to ones having air temerature and humidity. In addition, ANN-based PMV control logic conditioned the indoor PMV better within the specified range compared to the PMV control logic without ANN model.
3. Two predictive control logics incorporating ANN models reduced magnitude of overshoots and undershoots out of specified ranges for air temperature, humidity, and PMV.
4. Two predictive control logics reduced energy consumption for many cases although not as significant as expected.

In conclusion, the proposed thermal control strategy, i.e., a framework of control logic and predictive control embedded therein, has substantial potential for enhancing thermal comfort but does not have the significant energy efficiency for single-family homes.

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