Thermostat/Hygrometer vs ANN-Based Predictive/Adaptive Environmental Control Strategies

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Abstract
This study tested the feasibility of employing artificial neural network (ANN)-based predictive and adaptive control logics to improve thermal comfort and energy efficiency through a decrease in over- and under-shooting of control variables. Three control logics were developed: (1) conventional temperature/humidity control logic, (2) ANN-based temperature/humidity control logic, and (3) ANN-based Predicted Mean Vote (PMV) control logic. Analysis of the thermal chamber tests revealed that the ANN-based predictive temperature/humidity control logic provided greater periods of thermal comfort than that of the conventional logic by 0.3 to 5.1 percentage points for air temperature and 0.2 percentage point for humidity as well as a reduction in over-shoots and under-shoots. In addition, the ANN-based PMV control logic provided significantly better PMV conditions than both temperature and humidity based control logics. In most cases, ANN-based controls demonstrated a reduction in electricity consumption by 11.3% to 14.0% compared to non-ANN-based control logics, resulting in reduced fan usage and air circulation.

Keywords: thermal comfort, humidity control, artificial neural network, predictive control, adaptive control

Introduction

With its simplicity, thermostat- and hygrometer-based controls are the most widely used thermal control methods for residential buildings. However, this conventional method presents two problems in maintaining a comfortable indoor thermal environment. The first issue is the inability to take into account the building's thermal inertia and the control system's time lag associated with over and undershoots of thermal factors beyond the comfort range. This can lead to unnecessary system operation and energy consumption. The second problem arises from limiting performance to just two thermal variables (air temperature and humidity) when a number of other variables impact thermal comfort as evidenced in calculating the PMV (Predicted Mean Vote).

To address problems caused by over- and undershoots, new approaches to predictive control have been studied using artificial intelligence such as ANN (Artificial Neural Network). Yeo et al. (2003) developed an ANN model for predicting the optimal start time of a heating system for restoring interior temperature to a comfortable level by the start of business hours. Yang et al. (2000) designed a similar model but for predicting the amount of time for interior temperature to drop down to the lower limit of the comfort range. Employing these control logics with the heating system resulted in improved thermal comfort and energy efficiency for the test office buildings. For residential thermal controls, Morel et al. (2001) and Lee et al. (2002) applied ANN models to residential water heating systems and radiant floor heating systems. Gouda et al. (2006) investigated Fuzzy-ANN incorporation for a radiant heating device resulting in a significant reduction of temperature overshoots and energy consumption compared to the PI controller. ANN models were also applied for the optimal control of cooling devices. Ben-Nakhi et al. (2002) developed an ANN model for predicting end-of-setback moment for air-conditioning resulting in accurate control and ease of use.

Moon et al. (2009) investigated PMV control in residential buildings using ANN. The researchers developed a thermal control framework and ANN-based advanced logics for conditioning based on air temperature, humidity, and PMV. The performance of the control logics with setback were numerically tested using the IBPT (International Building Physics Toolbox). The tests identified the potentials for improving thermal conditions using ANN-based environmental controls.

Objectives

This study aimed at experimentally testing the performance of the three control logics developed by Moon et al. (2009) and identifying the optimal logic in terms of thermal comfort and energy efficiency. The tested control logics were: (1) conventional temperature and humidity control logic, (2) ANN-based temperature and humidity control logic, and (3) ANN-based PMV control logic. The ANN-based logics are predictive and adaptive methods of control. Experimental data from this study coupled with the previous study's computational analysis can provide further evidence of the potential of the proposed control logics for residential thermal control.

Methods

The three control logics tested for this study are shown in Figures 1, 2, and 3. Figure 1 shows the process for a conventional non-ANN-based temperature and humidity control logic. Figure 2 shows the process for a predictive and adaptive ANN-based temperature and humidity control logic. This model independently controls air temperature and humidity using ANN predictions from two ANN models, temperature and humidity. Figure 3 shows the process for a predictive and adaptive ANN-based PMV control logic. For this study, the following values were applied in calculating the PMV, 1.0 Met and 1.0 clo for winter and 1.0 Met and 0.5 clo for summer. Three identical feed-forward and back-propagation ANN models were developed for this study and details are provided in Table 1. Since there is not a fixed scientific solution for the design of an optimal ANN model, this study employed the empirical solutions proven in the previous studies [Moon J. W. et al (2009), Datta, D. et al (1997), Kalogirou, S. A. et al (2000), Yang I. H. et al (2003), Yang, J. et al (2005), MathWorks (2005)]. The logics were developed using Matlab's Neural Network toolbox.

The control logics were tested in a thermal chamber built inside a climate controlled building. Figures 4 and 5 illustrate the layout of the thermal chamber and structure of the applied control system. A radiant water heater, air conditioner, humidifier and dehumidifier were used to control the indoor climate. The control logics were tested under two conditions, heating/humidification (winter) and cooling/dehumidification (summer), for five days each with setbacks. Setbacks employ night and daytime setback of thermal factors to conserve energy. Figure 6 shows the comfort ranges and periods of the setback for air temperature, humidity and PMV.

Results and Discussion

The performances of the control logics were analyzed in terms of (1) duration of comfort period, (2) ratio and magnitude of overshoots and undershoots, and (3) energy consumption.

Duration of Comfort Period

Figures 7 and 8 show the duration the three control logics were able to maintain the comfort range under both heating/humidification and cooling/dehumidification operations. The ANN-based temperature/humidity control logic improved the comfort period of air temperature by 5.1 percentage points (86.2% to 91.3%) compared to the non-ANN-based temperature/humidity control logic during heating/humidification operations and by 0.3 percentage point (93.1% to 93.4%) during cooling/dehumidification operations. This difference between the heating and cooling operations was due to the greater time lag of the radiant heating system compared to the cooling system. Improvement over humidity was only 0.2 percentage point (98.0% to 98.2%) during heating/humidification operation. For cooling/dehumidification operation both logics maintained humidity comfort for 100% of the time. The ANN-based PMV control logic better maintained optimal PMV values (-0.5 to +0.5) than the two other temperature/humidity based control logics. Comfort was maintained 85.3% and 58.7% of the time during the heating/humidification and cooling/dehumidification operations respectively.

Overshoots and Undershoots

Overshoots and undershoots of air temperature and humidity were analyzed using Equations 1 and 2. The stability of thermal comfort factors for the non-ANN- and ANN-based control logics were compared using the ratio and magnitude of the over and undershoots.

$$R\ (\%) = N_O / N_T * 100 \qquad \text{(Eq. 1)}$$

Where,

R: Ratio of overshoots or undershoots outside the specified comfort range

N_O: number of overshoots or undershoots outside the specified comfort range

N_T: total number of overshoots or undershoots

$$M\ (^{\circ}C*\text{minutes or }\%*\text{minutes}) = \sum(\Delta \times t) \qquad \text{(Eq. 2)}$$

Where,

M: magnitude of overshoots or undershoots outside the specified comfort range

Δ: degree of overshoots or undershoots outside the specified comfort range

t: duration time of overshoots or undershoots outside the specified comfort range

The ratios of overshoots and undershoots for air temperature using the non-ANN-based control logic were all 100.0% while the ANN-based control logics mostly resulted in an average of 80.9% (Table 2). The magnitude of shoots was also reduced by the ANN-based control logic except for the overshoots during the cooling/dehumidification operation in which it increased from 1.90^{o}C to 2.03^{o}C*minutes (Table 3). Analysis of the ratio and magnitude of overshoots and undershoots indicates that the ANN-based control logic can better maintain consistant thermal conditions within the user specified ranges when using heating/cooling equipment having some time-lag.

Energy Consumption

Compared to the non-ANN-based control logic, the ANN-based temperature/humidity control logic saved energy on heating by 11.3% (from 10,425Wh to 9,250Wh) and humidification by 14.0% (from 300Wh to 258Wh) during the heating/humidification operation (Figure 9). For the cooling/dehumidification operation, the energy savings and reduced fan operation was 11.7% (from 962Wh to 849Wh) (Figure 10). ANN-based PMV control logic consumed more energy during both heating/humidification and cooling/dehumidification operations than the ANN- and non-ANN-based temperature/humidity control logics (Figures 9 and 10).

Conclusions

The main findings of this study are six fold.

- The predictive temperature/humidity control logic using ANN maintained more comfortable air temperature conditions than the conventional non-ANN-based temperature/humidity control logic. The predictive logic was more effective when applied to cooling/heating equipment with a large thermal lag effect, such as a radiant water heater.
- On the other hand, the comfort period of humidity was not significantly improved by the predictive logic. This may have been due to the humidity sensor's accuracy being only ±2%. Normal averaging method is suggested to reduce errors associated with collected sensor data.
- ANN-based PMV control logic better maintained optimal PMV conditions that the temperature/humidity based control logics.
- The predictive temperature and humidity control with ANNs stabilized better the thermal conditions than the conventional logic. The ratio and magnitude of over- and undershoots

of air temperature and humidity were generally reduced by the predictive logic even though an exceptional case for a device with insignificant time lag effect (A/C).

- ANN-based temperature and humidity control logics were generally more energy efficient. In particular, it was more energy efficient when using equipment with a higher thermal lag such as a radiant water heater.
- PMV-based control logic consumed more energy than temperature/humidity based control logics for both operating conditions due to the higher specified comfort range for PMV during the heating/humidification operation and the narrower comfort range for PMV during the cooling/dehumidification operation.

In conclusion, the predictive control of air temperature and humidity using ANN-based control logics has great potential for enhancing thermal comfort and energy efficiency in residential buildings. However, while the predictive control of PMV using ANN-based control logics improved overall thermal comfort, energy efficiency was lower than the ANN- and non-ANN-based air temeprature and humidity control logics. Thus, further study is warranted in investigating the value of improving thermal comfort (i.e. increased productivity) at the expense of increased energy consumption brought about by the ANN-based PMV control logic.

Acknowledgments

This work was supported by a grant from the Korean Ministry of Education, Science, and Technology (The Regional Core Research Program/Biohousing Research Institute) and the Biohousing Research Center.

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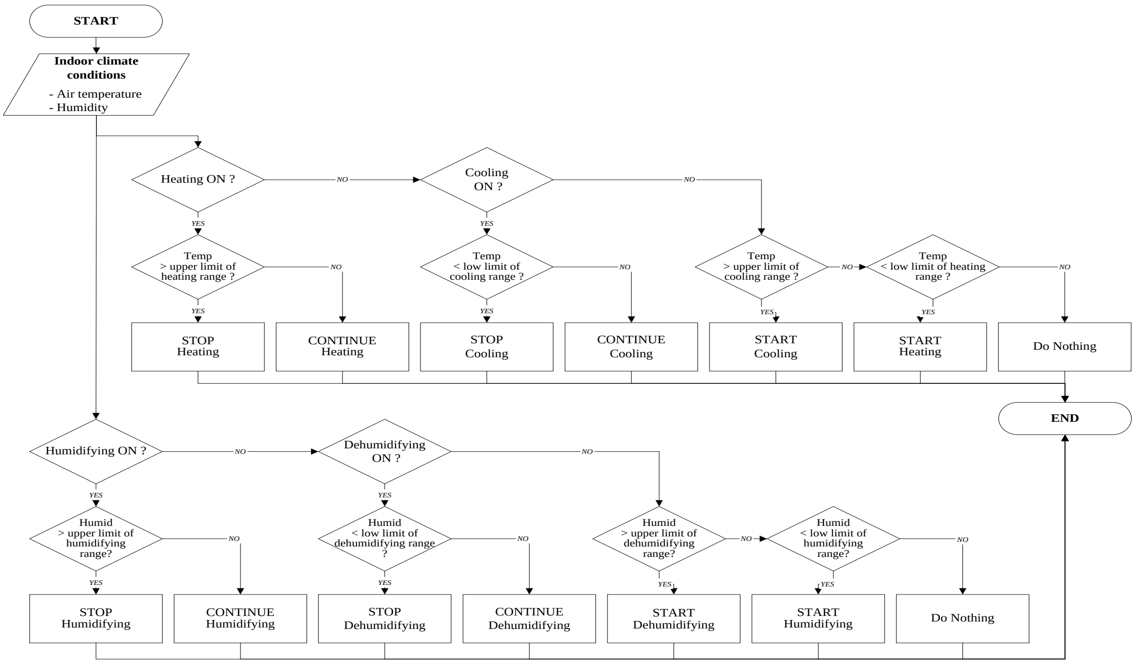

Fig. 1 Conventional non-ANN-based temperature/humidity control logic

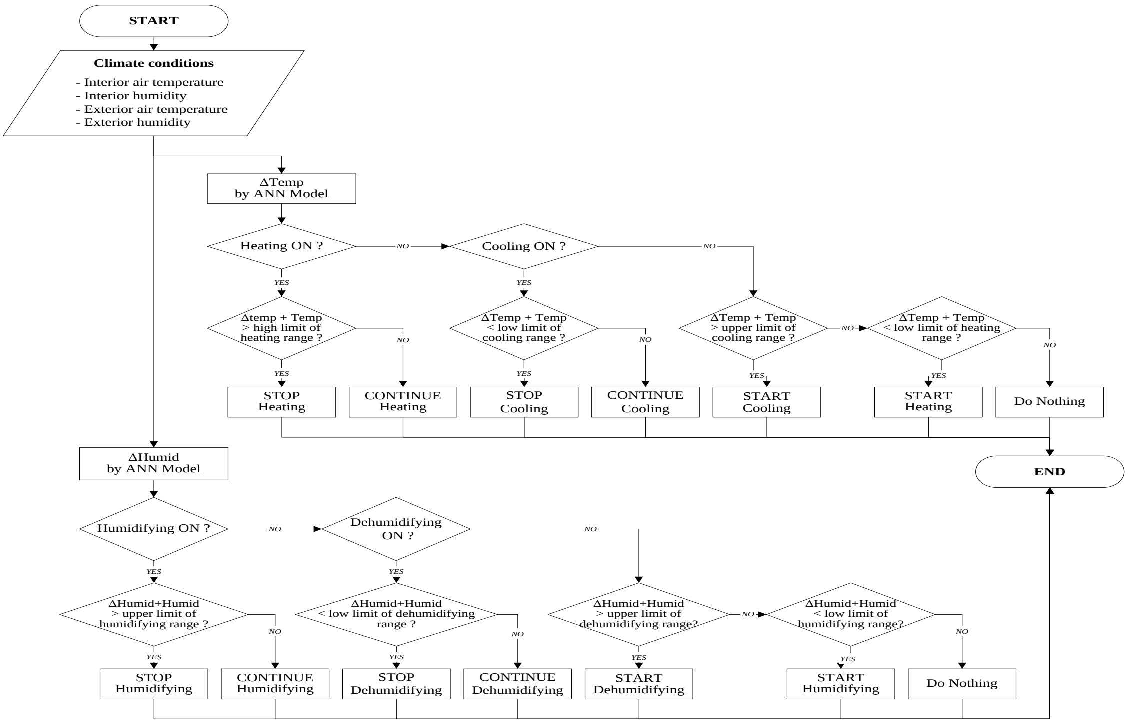

Fig. 2 ANN-based temperature/humidity control logic

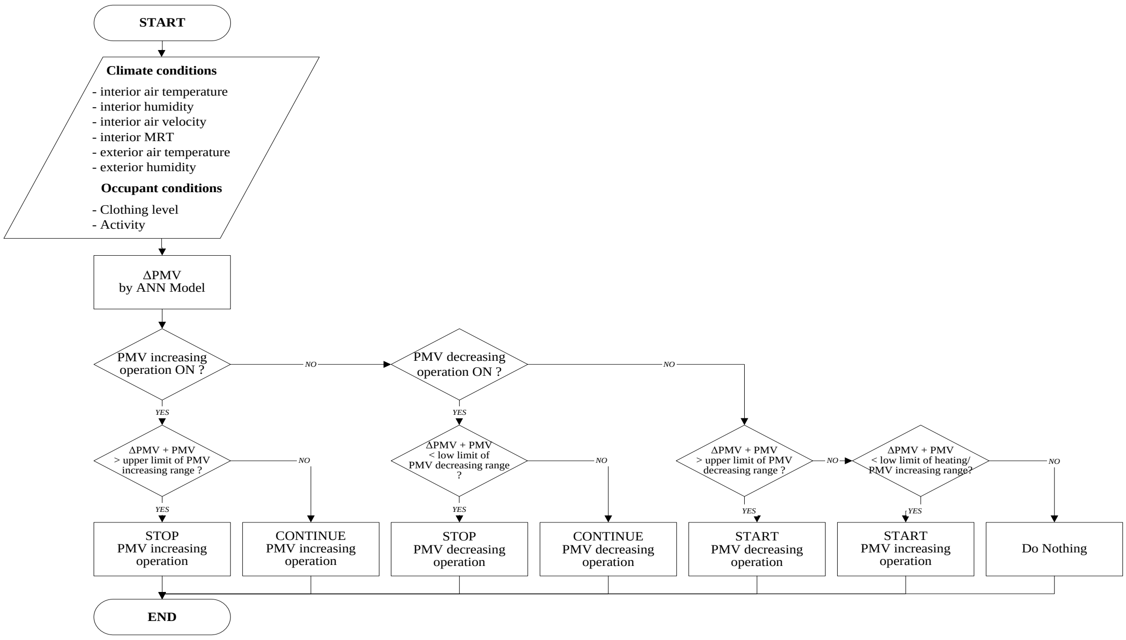

Fig. 3 ANN-based PMV control logic

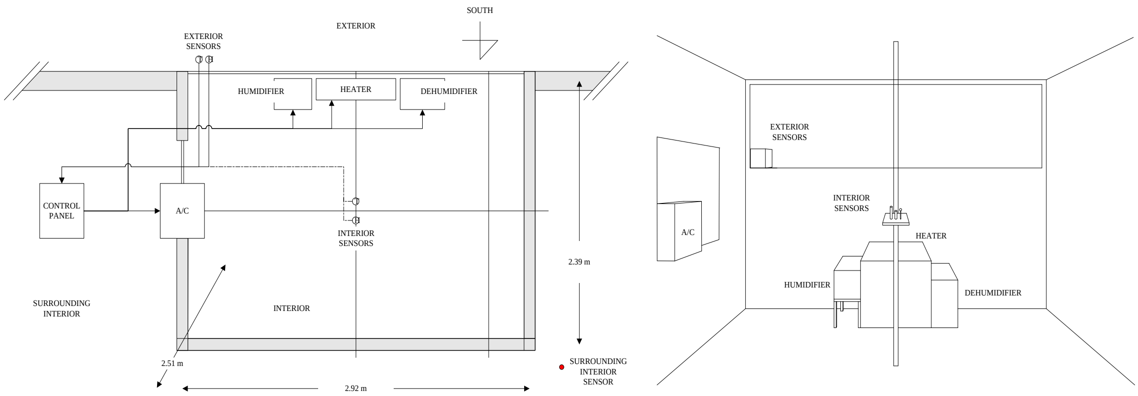

Fig. 4 Plan (left) and perspective (right) of thermal chamber

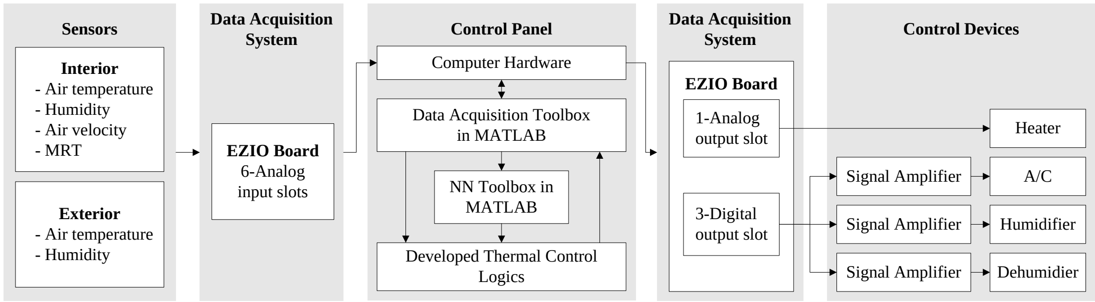

Fig. 5 Structure of the applied system

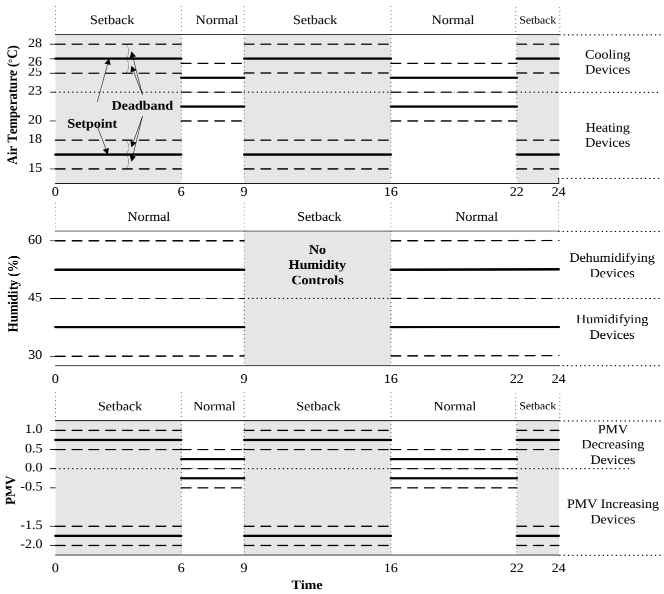

Fig. 6 Comfort ranges and periods of setback for air temperature, humidity, and PMV

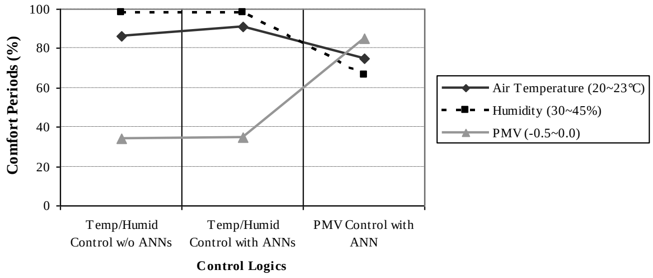

Fig. 7 Duration of comfort period during heating/humidification

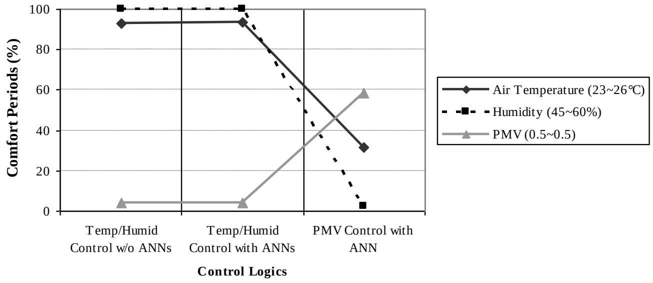

Fig. 8 Duration of comfort period during cooling/dehumidification

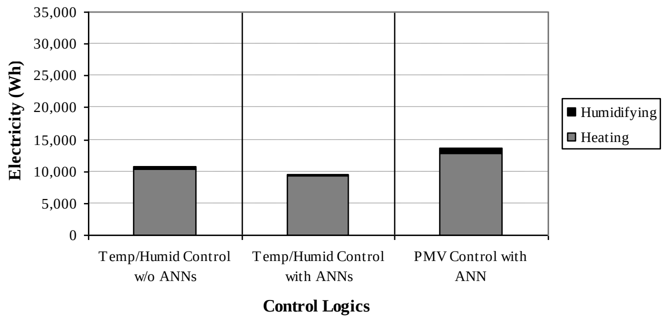

Fig. 9 Energy consumption (Wh) during heating/humidification operations

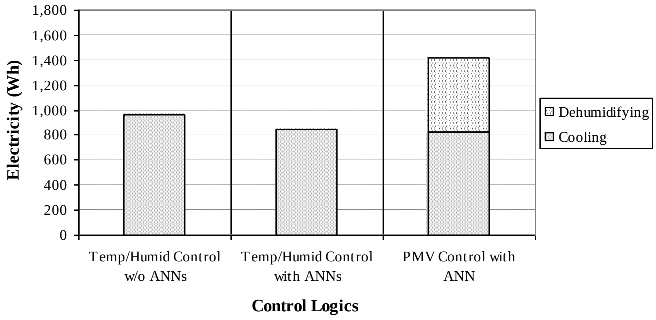

Fig. 10 Energy consumption (Wh) during cooling/dehumidification operation

Table 1 Description of developed ANN models

Structure	Input Layer	► Number of neurons: 8 1. exterior air temperature 2. exterior air temperature change from the preceding hour 3. exterior humidity 4. exterior humidity change from the preceding hour 5. interior air temperature 6. interior air temperature change from the preceding ten minutes 7. interior humidity 8. interior humidity change from the preceding ten minutes
	Hidden Layer	► Number of neuron: 17 using $N_h = 2 \times N_i + 1$ [Datta, D. et al (1997), Yang, J. et al (2005a)] Where, N_h: number of hidden neurons N_i: number of input neurons
	Output Layer	► Number of neuron: 1 (ΔTemperature, ΔHumidity, and ΔPMV, respectively)
Training Method		► Number of data set: 160 using $N_d = (N_h - (N_i + N_o)/2)^2$ [Kalogirou, S. A. et al (2000)] Where, N_d: number of data sets N_i: number of input neurons N_h: number of hidden neurons N_o: number of output neurons ► Obtained from the pre-test ► Type: sliding-window method ► Training goals: 0.1℃ for air temperature 0.1% for humidity 0.1 for PMV ► Epoch: 1,000 times ► Learning rate: 0.75 ► Momentum: 0.9 ► Algorithm: Levenberg-Marquardt [MathWorks (2005)]

Table 2 Ratio (%) of overshoots and undershoots of thermal factors outside the specified comfort ranges.

Seasons	Thermal Factors	Ratios of Shoots	Control Logics	
			Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating & Humidifying	Air Temperature	Overshoots (%)	100.0	**66.7**
		Undershoots (%)	100.0	**88.9**

Season	Humidity	Overshoots (%)	100.0	**85.7**
		Undershoots (%)	100.0	**85.7**
Cooling & Dehumidifying Season	Air Temperature	Overshoots (%)	100.0	**75.0**
		Undershoots (%)	100.0	**83.3**
	Humidity	Overshoots (%)	-	-
		Undershoots (%)	-	-

Table 3 Magnitude of overshoots and undershoots of thermal factors outside of specified comfort ranges.

Seasons	Thermal Factors	Magnitudes of Shoots	Control Logics	
			Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating & Humidifying Season	Air Temperature	Overshoots (˚C*minutes)	29.43	**9.21**
		Undershoots (˚C*minutes)	-10.34	**-9.17**
	Humidity	Overshoots (%*minutes)	5.99	**5.39**
		Undershoots (%*minutes)	-2.55	**-2.06**
Cooling & Dehumidifying Season	Air Temperature	Overshoots (˚C*minutes)	**1.80**	2.03
		Undershoots (˚C*minutes)	-3.66	**-2.75**
	Humidity	Overshoots (%*minutes)	-	-
		Undershoots (%*minutes)	-	-