ANN-BASED MODEL-FREE THERMAL CONTROLS FOR RESIDENTIAL BUILDINGS

by

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ABSTRACT

This research aimed to develop an Artificial Neural Network (ANN)-based advanced thermal control method for creating more comfortable thermal environments in residential buildings. The proposed control method, which consisted of a thermal control logic and system hardware framework, was designed to improve residential thermal environments through the reduction of thermal imbalance in various rooms; the achievement of thermal comfort considering humidity or PMV as a control variable; and the reduction of overshoots and undershoots of air temperature, humidity and PMV using ANN-based predictive and adaptive control.

In the control logic framework, four logics were employed for the residential thermal controls: (1) temperature and humidity control without ANNs as a conventional method, (2) PMV control without ANN, (3) temperature and humidity control with ANNs, and (4) PMV control with ANN. In addition, the system hardware framework was developed using sensors, data acquisition systems, a control panel, and building climate control systems.

The performance of four developed control logics and system hardware was tested through computer simulation incorporating IBPT (International Building Physics Toolbox) and MATLAB, and through experiment. A typical two-story single-family home was modeled for the computer simulation while a thermal chamber was built for the experiment. Variables for the simulation were (1) the change of building conditions such as orientations, R-values for walls, the roof and windows, and window-wall-ratio, and (2) disturbances such as the change of internal load and ventilation rate, the application of setback, the change of setpoint, and the extreme change of exterior thermal conditions. Variables for the experiment were application and non-application of setback.

The study reveals that ANN-based predictive and adaptive control strategies created more comfortable thermal conditions than ones without in terms of increased comfort period of air temperature, humidity, and PMV. This improvement was through

the reduced ratio and magnitude of overshoots and undershoots out of the specified comfort ranges. In many cases, ANN-based strategies consumed less energy for building climate control systems although not as significantly as expected. Based on this study, it can be concluded that ANN-based predictive and adaptive climate control strategies can improve thermal comfort in residential buildings.

CHAPTER I

THERMAL CONTROL FOR SINGLE-FAMILY REISDENTIAL BUILDINGS

As the time modern people spend in buildings increases to around 90%, the indoor environmental quality (IEQ), which describes the environmental (e.g., physical, psychological, and sociological) conditions of interior spaces, has a significant role in determining the life quality of occupants. Comfort, health, and productivity are deeply associated with the IEQ, and the quality of occupant behavior is, therefore, significantly affected by it [Berglund, B., et al. (1992), Brasche, S., et al. (2001), Fisher, P.H., et al. (1998), Garrett, M. H., et al. (1998), Stenerg, B., et al. (1993)].

Efforts have been devoted to supplying a comfortable IEQ. Standards and guidelines for IEQ, for physical conditions in particular, have been published by diverse governing bodies such as American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) and Illuminated Engineering Society of North America (IESNA) [ASHRAE (2004), (1999a), (1999b), IESNA (2000)]. In addition, the advanced IEQ monitoring and controlling strategies have been introduced for creating a comfortable indoor environment. The DDC (Direct Digital Control)-based automatic control strategy in a network space, also known as BA (Building Automation), was developed for advanced control of HVAC, lighting, transportation, and entertaining devices.

The environmental quality of residential buildings is increasingly recognized as important with the increase of people spending time at home. “Home office” or “working home” are widespread concepts, which lead people to stay home. Under these conditions, the home is regarded as a space for not only consumption, but also production. In order to create a comfortable environment in this home space, a number of projects associated with “smart home” or “home automation” have been conducted, which have reinforced the functions of home in an automated way. New homes, as a result, are now equipped with automatic devices for heating, cooling, ventilation and lighting (e.g., use of a thermostat and occupancy sensor), protocols for user interaction to domestic systems, telecommunicating systems for communicating to the outside world, and entertaining and health care devices [Harper, R (2003), Junestrand, S. (1999), (2004), Larson, K., et al. (2005), Larson, K. (2005), AHRI (2006), Abowd, G. D., et al (2000), (2002)]

1.1 Issues in Residential Buildings

Residential buildings have various issues regarding indoor environmental quality (IEQ). Thermal performance is a principal component of IEQ, and its issues are deeply related to determining the domestic IEQ. In addition, the productivity of residential buildings is an issue of concern in recent days with the concept of the home office. At the same time, energy has been an important issue since the energy crisis in 1970s. Details of these issues are illustrated in Figure 1.1.

1.1.1 Thermal Performance

The first issue regarding the thermal performance of residential buildings is the thermal imbalance due to the limited number of thermostat applications. In general, each space of the residential building shows different thermal conditions. A thermostat is, however, located in a living room, and the operations of thermal control devices are dependent on it. Each space could experience, therefore, a thermal discomfort such as overheating or overcooling. One feasible way for improving this situation is to build a distributed sensor network and control logic in space, then to encourage user interactions (e.g., set the setpoint of air temperature and setback value and time) for system operation.

The next issue is thermal discomfort due to the overshoots and undershoots caused by the time-lag of the control systems and building thermal response. Time-lag means a certain period of time that is required for actually improving the thermal conditions in space when an operating signal reaches the control systems. For example, as the air temperature decreases the lower limit of the comfort range, the control logic sends a signal for operating a heating device. The heating device begins to work based on this signal; however, air temperature does not rise immediately, or would rather drops a little bit more then begin to rise. There are two primary reasons for this time-lag. The first reason is that systems require some time for actually working and having an impact on a space (e.g., time required for beginning to discharge heat to space by a radiant heating device). The second reason is that the space has thermal inertia which causes a delay of thermal response to the system work (e.g., time between the moment that heat begins to be discharged by a heating device and the moment that the air temperature of a space begins to rise). In order to reduce thermal discomfort due to the time-lag, a predictive control method is required, by which thermal control systems could begin to work before the thermal conditions do not reach the marginal level of the comfort range.

The last issue is that limited types of thermal factors are currently considered to be controlled. Air temperature is generally the only target while humidity is rarely controlled and the PMV is not counted to be controlled. Thermal discomfort, as a result, is created even though air temperature is comfortable. For example, occupants feel dry by a low humidity or feel cold by low PMV level in winter within a comfortable range of the air temperature. Therefore, integrated control logic and system hardware that include more diverse sensing devices need to be developed for controlling the thermal condition more completely (e.g., creating a comfortable PMV condition).

1.1.2 Energy

Buildings are a major source of energy consumption and greenhouse gas (GHG) emissions, and account for 48% of energy consumption and GHG emissions annually [Mazria, E. (2007)]. Of the energy consumed by residential buildings in 2001, which is 21.0% of energy consumption in all buildings, 53.2% was used for space heating and cooling purposes [EIA (2001)]. Therefore, the conservation of heating and cooling energy presents a major target for residential building energy conservation.

One of the solutions for reducing energy consumption in residential buildings is to increase the insulation level of envelopes. Heat loss and gain through envelopes could be decreased as the insulation levels of walls, roof, foundation, and windows are increased.

Proper insulation level is recommended for the residential buildings by ASHRAE [ASHRAE (2004)].

The proper application of thermostat setting is recommended for reducing energy consumption. Setpoint temperature for heating and cooling systems needs to be set properly for preventing overheating and overcooling. In addition, nighttime and daytime setback modes are effective to reduce energy consumption. An intelligent thermostat, which recommends the optimal setpoint and setback, is necessary for energy efficiency.

A predictive control of thermal conditions could be one of the solutions for reducing energy consumption. Time-lag causes overheating or overcooling resulting in energy waste by unnecessary device operations. Overheating and overcooling can be reduced by the predictive control method, by which the operation of heating and cooling devices is determined before the thermal conditions reach the marginal level of comfort range. Therefore, a control logic which uses the predicted future thermal conditions in the algorithm needs to be applied for energy efficiency.

1.1.3 Productivity

In order to increase occupant well-being, the IEQ of a home needs to be controlled more comfortably. For example, it is necessary to control the thermal quality of a working area in the home during the daytime as well. Devices for the localized thermal control will be installed for comfort and energy efficiency. In particular, a zonal control strategy, which consists of distributed thermostats and a zone damper, will effectively satisfy the localized thermal requirements [The Zoning System Company (2004)]. The working area during the daytime, as a result, will be thermally comfortable with the efficient energy consumption.

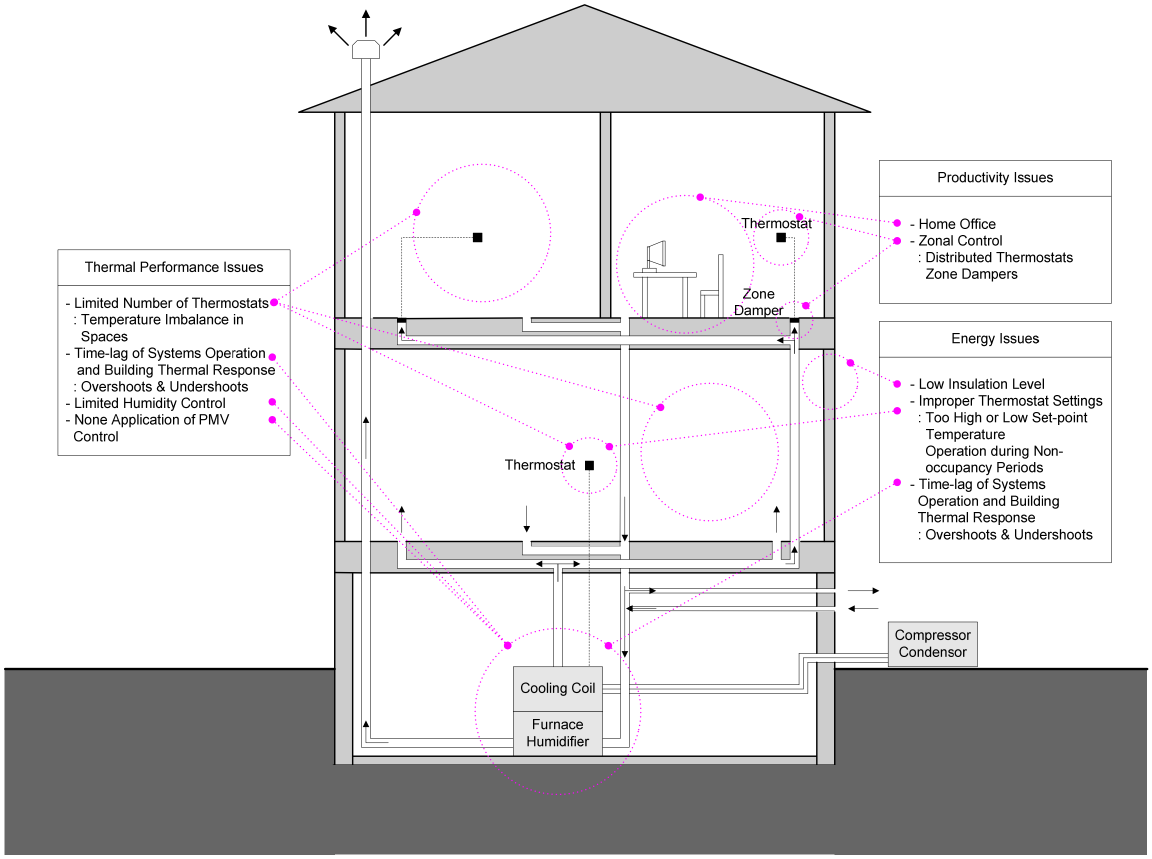


Figure 1.1 Issues Associated with IEQ in Residential Buildings

1.2 Thermal Comfort

Thermal comfort is defined as “that condition of mind which expresses satisfaction with the thermal environment” [ASHRAE (1966)]. It is a complex perception of the environment that involves the physical environment as well as physiological and psychological state of a person. Since thermal comfort is one of the primary factors that determine the IEQ, a proper control of thermal environment is an important task to be conducted for improving IEQ and occupant comfort, health, and productivity [Parsons, K. C. (2003)].

1.2.1 Factors of Thermal Comfort

Factors of thermal comfort can be classified into two categories—primary and secondary. The primary factors are conditions of the physical environment while the secondary factors are close to the psychological parameters [Spengler, J. D., et al. (2000)].

1.2.1.1 The Primary Factors

The primary factors of thermal comfort consist of two groups—environmental and personal. The environmental factors are composed of the four environmental parameters: air temperature (dry-bulb temperature, DBT), mean radiant temperature (MRT), relative humidity (RH), and air velocity (air speed or movement). And, the personal factors consist of the human metabolic rate and insulation level of clothing. These factors are directly affecting to determine the occupant thermal comfort [Parsons, K. C. (2003), Spengler, J. D., et al. (2001), ASHRAE (1997)].

The environmental factors and personal factors can be described as follows.

- Air temperature: Air temperature means the dry bulb temperature (DBT) which is the most significant factor determining the energy balance, comfort, discomfort, thermal sensation, and perception of air quality. It can be measured by liquid-in-glass thermometers, thermocouples, and resistance temperature devices [Spengler, J. D., et al. (2001)].
- Mean radiant temperature (MRT): Radiant temperature is the temperature of the object or surface, which radiates heat to other objects (e.g., the human body). Mean radiant temperature (MRT) is the average of radiant temperatures that are facing an occupant: therefore, not only surface temperature, but also the geometry of a space and the occupant location are involved in calculating the MRT [3]. MRT is one of the essential parameters to determine thermal comfort. For example, occupants feel cold (discomfort), even in the comfortable DBT space, when they are surrounded with cold

surfaces. MRT can be calculated with the surface temperatures and angles to surfaces (Equation 1) [Kim, J. J. (2004), Spengler, J. D., et al. (2001)].

MRT (°C or °F) = $(T_1*\theta_1 + T_2*\theta_2 + T_3*\theta_3 + T_4*\theta_4) / 360°$ .... (Equation 1.1)

Where,

T1, T2, T3, T4: surfaces' temperature facing to occupant (°C or °F)

$\theta_1, \theta_2, \theta_3, \theta_4$: angles occupant facing to each surfaces (°)

- Relative humidity (RH): Relative humidity is the percentage that describes the current amount of water vapor over the amount of the saturated water vapor in the air. It affects the heat balance of body by determining the amount of evaporation on the skin. Since a human body evaporates less vapor from the skin in a higher RH condition, occupants may feel hotter (discomfort) in the higher RH space even with the same DBT. RH is calculated by Equation 1.2 [Kim, J. J. (2004), Spengler, J. D., et al. (2001)].

RH (%) = $W_{moisture} / W_{max} * 100$ .... (Equation 1.2)

Where,

$W_{moisture}$: weight of moisture in air

W_{max}: maximum of possible moisture in air

- Air velocity (air speed): Air velocity originates from air movement. It can be measured by an omni-directional anemometer, which detects air movement in all directions. Air velocity, in general, is around 0 to 0.5 m/s in a mechanically controlled space. Proper air movement reduces the heat stress through the evaporation on the skin in a space of low RH. High speed air movement, however, causes discomfort due to dryness in the respiratory organs, ocular systems, and skin [Spengler, J. D., et al. (2001)].
- Metabolic rate: Metabolic rate is a rate of heat discharged from the human body by physical activities such as office activities, sports, and various occupational activities. The unit of metabolic rate is W/m^2 or MET. 1 MET is

identical to 58.2 W/m^2, which is the amount of heat discharged from a sedentary average-sized adult (1.8m^2 of body surface area). Metabolic rate differs by activity: for example, the rate is 1.0 MET for reading, 1.2 MET for sitting or typing, 3.0 MET for dancing, 4.0 MET for cycling or tennis, and 6.0 MET for going up stairs. This rate for the same activity, however, can be different by gender, age, and body size. Metabolic rate can affect occupant thermal comfort. For example, a person with a higher metabolic rate feels hotter (discomfort) for the same environmental conditions [Spengler, J. D., et al. (2001), ASHRAE (1997)].

- Clothing: Clothing protects heat loss by acting as the body's insulation and helps skin maintain a stabilized temperature. In addition, the effectiveness of the moisture evaporation on the skin is affected by clothing—the fabric moisture permeability. Insulation and permeability levels contribute to the occupant thermal comfort. The unit of clothing level is CLO. 1 CLO is 0.155 m^2*K/W, when a person wears a business suit ensemble. CLO is given for various clothing components such as 0.24 for trousers, 0.14 for skirt, 0.19 for short sleeve shirt, 0.25 for sweater [Parsons, K. C. (2003), ASHRAE (1997)].

1.2.1.2 The Secondary Factors

The secondary factors consist of psychological parameters such as age, gender, acclimation, seasonal and circadian rhythms. Those would have influence on determining the thermal comfort. Their impacts, however, are not as significant as the primary factors [Parsons, K. C. (2003), ASHRAE (1997)].

The secondary factors can be described as follows.

- Age: In spite of the general belief that older people prefer a higher temperature than younger people, the comfort votes of elderly and young adults showed the same results when they were in the same thermal conditions with same clothing level. Instead, the reason of the elder people's preference for the higher temperature was probably caused by the lower activity level, which has a lower metabolic rate [Parsons, K. C. (2003), ASHRAE (1997)].

- Gender: Similar to the age, gender also did not cause different vote results for the thermal comfort [ASHRAE (1997)]. However, other research indicated that, even though it was subtle, females felt cooler than males in the cold conditions [Breslin, R. (1995)].
- Acclimation: Humans change their physical responses to the thermal conditions after being exposed to a new environment for a certain period. For example, when they move to hotter conditions, they begin to sweat earlier and more after a certain amount of time, compared to the earlier days, in order to maintain the thermal balance of the body. This phenomenon is called the acclimation of the body. Because of this effect, different subjects from various thermal conditions show the same thermal comfort preference after a certain period of being exposed to new thermal conditions. The racial issue caused by the different thermal conditions, therefore, would not be able to affect or determine the thermal comfort ranges [Spengler, J. D. (2001)].
- Seasonal and Circadian Rhythms: There was not any different result of thermal comfort vote between summer and winter. This means that people do not require different thermal comfort ranges for the different seasons. That is supported by the fact that humans are not able to change their body temperature for adapting to the ambient temperature. In addition to this, people showed the same preference for the comfortable air temperature over the course of a day, except they slightly preferred warmer conditions before having lunch. Seasonal and circadian factors, therefore, do not seem to significantly influence the thermal comfort range [ASHRAE (1997), Fanger, P. O. (1970)]. On the contrary, the other research indicated that the seasonally changing ambient temperature could affect the thermal comfort range. It argued that the change of behavioral responses to optimize comfort such as change of the clothing level and the body posture need to be taken into account for determining the thermal comfort range. For example, the comfort range of air temperature in winter is lower than that of in summer because people generally wear more clothes in winter [Dear, R. D., et al. (1997)].

- Other Factors: Fanger, P. O. tried to find the influence of body build, ethnic differences, surrounding color, food, crowding, and air pressure on the thermal comfort. He concluded that these factors were not significantly related to thermal comfort [Fanger, P. O. (1970)].

1.2.2 Models of Thermal Comfort

Models for describing thermal comfort are classified into two categories—static and adaptive. There is a difference in their embedded assumptions about how humans act toward the environment: passively or actively. In the static models, human are assumed as passive subjects who do not do any efforts to change the environment, so that the thermal comfort range is constant. On the contrary, in the adaptive models, humans try to adapt themselves to a new environment through behavioral, physiological, and psychological adaptation as active subjects. Therefore, the thermal comfort range is adaptive based on the change of the surrounding environment (e.g., change of the ambient temperature). As a result, the thermal comfort range of each model is different, and the energy consumption for thermal conditioning, therefore, is different as well [Spengler, J. D. (2001)].

Thermal sensation (TS) models, predicted mean vote (PMV), and two node models are summarized in detail as the static models followed by the recent study on the adaptive models in subchapters.

1.2.2.1 Thermal Sensation (TS) Models

Thermal sensation (TS) is “the conscious perception of the body’s effort to regulate body temperature” [Spengler, J. D. (2001)]. That is to say, it is the value that describes the psychological state responding to the physiological conditions. On a cold winter day, for example, skin shivers as a physiological condition. By this body expression, humans feel coldness, and behave in ways that allow them to maintain their body temperature. TS, here, is the value to describe how cold human feels in a psychological way.

Numerical scales are used to indicate the psychological thermal sensation. Several thermal sensation scales are given in Table 1.1. The shaded parts correspond to assumed comfortable perceptions. ASHRAE scale is the commonly used seven-point thermal sensation scale. The Bedford scale introduced in 1936 is not frequently used because of the similarity with the ASHRAE scale. The thermal acceptability scale, the thermal preference scale by McIntyre (1980), and the six-point general comfort scale are other similar methods to express the psychological values for responding to the physiological environmental conditions [Spengler, J. D. (2001)].

Scale	Response						
ASHRAE	-3 Cold	-2 Cool	-1 Slightly Cool	0 Neutral	+1 Slightly Warm	+2 Warm	+3 Hot
Bedford	Much too cool	Too cool	Comfortably cool	Neither warm nor cool	Comfortably warm	Too warm	Much too warm
Acceptability	Unacceptable		Acceptable			Unacceptable	
Preference (McIntyre)	Want warmer		No change			Want cooler	
General Comfort	Very uncomfor-table	Moderately uncomfor-table	Slightly uncomfor-table	Slightly comfortable	Moderately comfortable	Very comfortable	

Table 1.1 Rating Scales Commonly Used in Thermal Comfort Research [Spengler, J. D. (2001)]

ASHRAE presented equations for calculating TS as given in Table 1.2. Air temperature and vapor pressure are used in the calculation. In particular, the vapor pressure is calculated from the relative humidity. Thus, the air temperature and the relative humidity are determinants of TS value. In addition to this, TS value is affected by the gender and length of period exposed to the environment. The comfortable TS range is given between -0.5 and 0.5 [ASHRAE (1997)].

Exposure Period, h	Sex	Regression Equations T= dry-bulb temperature, °C P = vapor pressure, kPa
1.0	Male	Y = 0.220t + 0.233p – 5.673
	Female	Y = 0.272t + 0.248p – 7.245
	Combined	Y = 0.245t + 0.248p – 6.475
2.0	Male	Y = 0.221t + 0.270p – 6.024
	Female	Y = 0.283t + 0.210p – 7.694
	Combined	Y = 0.252t + 0.240p – 6.859
3.0	Male	Y = 0.212t + 0.293p – 5.949
	Female	Y = 0.275t + 0.255p – 8.622
	Combined	Y = 0.243t + 0.278p – 6.802

Table 1.2 Equations for Predicting Thermal Sensation (Y) of Men, Women, and Men and Women Combined [ASHRAE (1997)]

1.2.2.2 Predicted Mean Vote (PMV)

Predicted mean vote (PMV) is another type of model developed by Fanger for describing TS. It is a regression model based on the results of laboratory studies that aimed to investigate the relationship between each thermal factor and thermal sensation. Study subjects primarily consisted of college aged Caucasian males in a steady state environment [Fanger, P. O. (1970)].

PMV is a function of six thermal factors: air temperature, mean radiant temperature, relative humidity, air velocity, metabolic rate, and thermal resistance of clothing. Its index is based on the ASHRAE's psychophysical scale: +3 hot, +2 warm, +1 slightly warm, 0 neutral comfort, -1 slightly cool, -2 cool, and -3 cold. The acceptable thermal environment for general comfort is between -0.5 and +0.5. PMV is calculated by Equations 1.3 to 1.6 [ASHRAE (1997)].

$$PMV = (0.303e^{-0.036M} + 0.028)\{(M - W) - 3.05 * 10^{-3} [5733 - 6.99 (M - W) - p_a]$$
$$- 0.42[(M - W) - 58.15]\ 1.7 * 10^{-5} M(5867 - p_a) - 0.0014\ M (34 - t_a)$$
$$- 3.96*10^{-8} f_{cl} [t_{cl} + 273]^4 - (t_r + 273)^4] + f_{cl} h_c (t_{cl} \pm t_a)\} \text{ .... (Equation 1.3)}$$

Where,

$$t_{cl} = 35.7 - 0.028 (M - W) - I_{cl} \{(3.96 * 10^{-9} f_{cl} [(t_{cl} + 273)^4 - (t_r + 273)^4]$$

$+ f_{cl}h_c\,(t_{cl} - t_a)\}$ .... (Equation 1.4)

$h_c \;=\; 2.38\,(t_{cl} - t_a)^{0.25}$ or $= 12.1v^{0.5}$, whichever is greater .... (Equation 1.5)

$f_{cl} \;= 1.00 + 1.29I_{cl}$ if $I_{cl} \leq 0.078m^2k/W$, else $= 1.05 + 0.645\,I_{cl}$................ (Equation 1.6)

M: metabolic rate (W/m^2 of the body area)

W: external work (W/m^2 of the body area, = 0 in most cases)

I_{cl}: thermal resistance of clothing (m^2k/W)

t_a: air temperature (^oC)

t_r: mean radiant temperature (^oC)

v: air velocity relative to the body (m/s)

p_a: partial water vapor pressure (Pa)

t_{cl}: clothing surface temperature (^oC)

h_c: convective heat transfer coefficient (W/m^2k)

f_{cl}: ratio of clothed surface area to nude surface area

1.2.2.3 Two-Node Model

While the PMV model does not consider the effect of human physiological factors, the two-node model (TN) calculates thermal sensation by taking into account the physiological responses to changeable environment. It assumes that a human body consists of two different compartments—skin and core body. The core body temperature does not change significantly responding to the change of surrounding air temperature while the skin temperature tends to be adaptive to the surrounding air temperature. Thus, the mean body temperature changes based on the air temperature. Using this mean body temperature (t_b), the two-node model calculates thermal sensation (TSENS) and thermal discomfort (DISC) values with Equations 1.7 and 1.8, respectively. In these equations, the relationship between body temperature (t_b) and cold and hot set points ($t_{b,c}$, $t_{b,h}$) for the zone of evaporative regulation affects the thermal sensation results and thermal discomfort value. In addition, skin wetness is also considered for calculating thermal discomfort [ASHRAE (1997)]. The expression of TSENS and DISC is from -5 to +5 in which the negative and positive values represent the cool and warm side, respectively (Table 1.3) [ASHRAE (1997)].

TSENS: $0.4685(t_b - t_{b,c})$ when $t_b < t_{b,c}$

$4.7\eta_{ev}(t_b - t_{b,c}) / (t_{b,h} - t_{b,c})$ when $t_{b,c} <= t_b <= t_{b,h}$

$4.7\eta_{ev} + 0.4685(t_b - t_{b,h})$ when $t_{b,h} < t_b$.............. (Equation 1.7)

DISC: $0.4685(t_b - t_{b,c})$ when $t_b < t_{b,c}$

$4.7(E_{rsw} - E_{rsw,req}) / (E_{max} - E_{rsw,req} - E_{dif})$ when $t_{b,h} < t_b$ .... (Equation 1.8)

Where,

η_{ev}: evaporative efficiency (assumed to be 0.85)

t_b: mean body temperature (°C)

$t_{b,c}$: cold set point representing lower limit for zone of evaporative regulation (°C)

$t_{b,h}$: hot set point representing lower limit for zone of evaporative regulation (°C)

E_{max}: maximum evaporation when skin is completely covered sweat (W/m^2)

E_{rsw}: the rate of regulatory sweating (W/m^2)

$E_{rsw,req}$: heat loss by evaporation of sweat from skin surface (W/m^2)

Expressions	TSENS	DISC
+5	Intolerably hot	Intolerable
+4	Very hot	Limited tolerance
+3	Hot	Very uncomfortable
+2	Warm	Uncomfortable and unpleasant
+1	Slightly warm	Slightly uncomfortable but acceptable
0	Neutral	Comfortable
-1	Slightly cool	Slightly uncomfortable but acceptable
-2	Cool	Uncomfortable and unpleasant
-3	Cold	Very uncomfortable
-4	Very cold	Limited tolerance
-5	Intolerably cold	Intolerable

Table 1.3 Expressions of TSENS and DISC

1.2.2.4 Adaptive Thermal Comfort Model

Different from the static models, adaptive thermal comfort models take into account the occupant behavioral, physiological, and psychological adjustments for achieving thermal comfort based on the fundamental assumption that "If a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort." Those actions include (1) manipulation of clothing, and body movement as the behavioral adjustments, (2) the body's acclimation to new environment such as vasodilatation, vasoconstriction, shivering, and sweating as the physiological adjustments, and (3) the change of expectation for comfort based on the past experience as the psychological adjustments. These behaviors change internal heat generation or the heat loss from the body [Spengler, J. D. (2001), Nicol, F. (1993)].

The adaptive model concept is visualized in Figure 1.2. It indicates the relationship between air temperature recommended by ASHRAE and air temperature assumed by the adaptive model. While the ASHRAE recommended air temperature is static depending on the season, that of the adaptive model is changing based on the outdoor temperature and ASHRAE recommended indoor temperature. Since the indoor temperature by the adaptive model reflects the exterior temperature, it is able to reduce energy consumption and operational cost for systems, greenhouse gas emissions, peak demand, and the plant size [Spengler, J. D. (2001)]

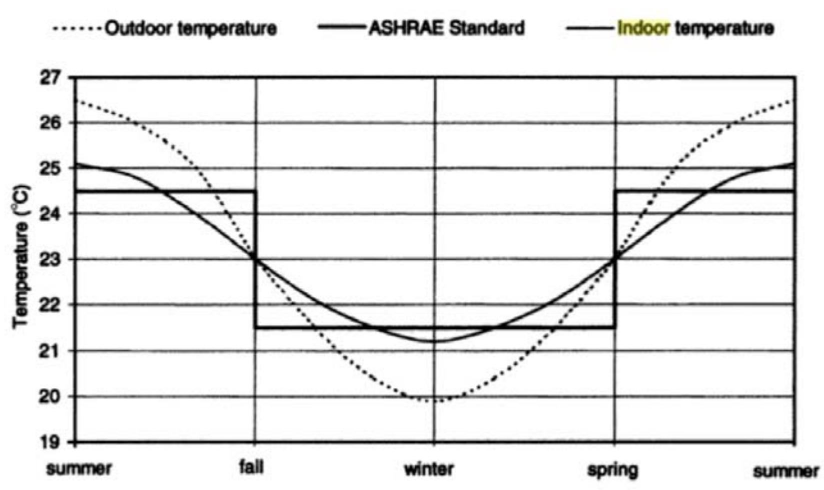


Figure 1.2 The Adaptive Model Concept [Spengler, J. D. (2001)]

Auliciems developed an adaptive model for calculating the neutral temperature which fits thermal comfort (Equation 1.9). The neutral temperature is achieved with ambient air temperature and mean monthly air temperature. It means that changeable ambient air temperature and mean monthly air temperature can affect the human's perception of the thermal comfort [Auliciems, A. (1989)].

$T_n = 9.22 + 0.48T_a + 0.14T_{mmo}$ .... (Equation 1.9)

Where,

T_n: neutral temperature (°C)

T_a: ambient air temperature (°C)

T_{mmo}: mean monthly air temperature (°C)

1.2.3 Standards and Guidelines

Standards and guidelines have been published for recommending comfortable thermal conditions. Comfort ranges of air temperature, humidity, and air velocity are summarized in Table 1.4. Seasonal variation of the comfort range is presented from many governing bodies, which allows a higher range in summer. Comfort ranges of air temperature and relative humidity from ASHRAE Standard 55-1992 were applied when the control logic was developed in this study (See Chapter 4 RESEARCH DESIGN) [OSHA (2004), SLOHS (2004), University of Sydney (2003), CSA (2000), DOS (1997), and ASHRAE (1992), (1981), (1966)].

Factors	Standards		Guidelines	
	Concentration	Governing Body	Concentration	Governing Body
Air Temperature	68~76°F	OSHA	68.5~75.5°F (winter, 30% RH) 74.0~80.0°F (summer, 30%RH)	DOS
	66.9~75.9°F, 19.4~24.4°C (at 50% RH)	ASHVE 1924	68.0~75.0°F (winter, 40% RH) 73.5~80.0°F (summer, 40%RH)	DOS
	22.7~25°C	ASHRAE Standard 55-1966	68.0~74.5°F (winter, 50% RH) 73.0~79.0°F (summer, 50% RH)	DOS
	20.0~23.5°C [winter]	ASHRAE Standard 55-1981	67.5~74.0°F (winter, 60% RH) 73.0~78.5°F (summer, 60% RH)	DOS
	22.5~26°C [summer]	ASHRAE Standard 55-1981	21~24°C (summer, optimum) 20~26°F (summer, acceptable)	U of Sydney
	68~75°F, 20~23.5°C (winter, clothing: heavy slacks, long-sleeve shirts, and sweaters	ASHRAE Standard 55-1992	19~22°C (winter, optimum) 18~24°F (winter, acceptable)	U of Sydney
	71F, 22°C (winter, optimum temperature, clothing: heavy slacks, long-sleeve shirts, and sweaters	ASHRAE Standard 55-1992	20~25°C [winter, 30% RH]	SLOHS
	73~79°F, 23~26°C (summer, clothing: light slacks, and short sleeve shirt)	ASHRAE Standard 55-1992	20~24°C [winter, 40% RH]	SLOHS
	76, 24.5°C (summer, opptimum temperature, clothing: light slacks, and short sleeve shirt)	ASHRAE Standard 55-1992	20~24°C [winter, 50% RH]	SLOHS
			20~23°C [winter, 60% RH]	SLOHS
			23~27°C [summer, 30% RH]	SLOHS
			23~26°C [summer, 40% RH]	SLOHS
			23~26°C [summer, 50% RH]	SLOHS
			23~26°C [summer, 60% RH]	SLOHS
Humidity	20~60% RH	OSHA	30~80% RH [summer]	CSA
	20~60% RH	ASHRAE Standard 55-1966	30~55% RH [winter]	CSA
	Dew point not exceed 16.7°C	ASHRAE Standard 55-1981	30~60% RH	DOS
	30~60% RH	ASHRAE Standard 55-1992		
	20~70% RH	CSA	40~60% RH	U of Sydney
Air Velocity	0.05~0.29 m/s	ASHRAE Standard 55-1966		
	~0.15 m/s [winter]	ASHRAE Standard 55-1981		
	~0.25 m/s [summer]	ASHRAE Standard 55-1981		
	~0.25 m/s	ASHRAE Standard 55-1992		

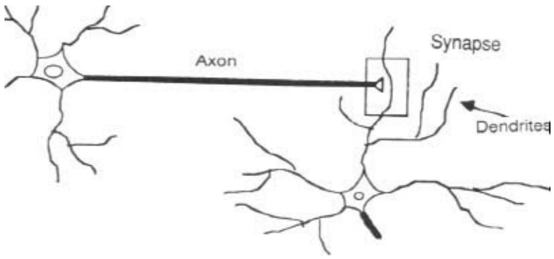
Table 1.4 Thermal Comfort Standards and Guidelines
(Glossary, ASHVE: American Society of Heating and Ventilating Engineers, ASHRAE: American Society of Heating, Refrigerating, air conditioning engineers, CSA: Canadian Standards Association, DOS: Division of Occupational Safety, OSHA: Occupational Safety and Health Administration, SLOHS: Saskatchewan Labor Occupational Health and Safety, U of Sydney: University of Sydney)

1.3 Artificial Neural Network (ANN) in Building Thermal Control

Artificial-Neural-Network (ANN), which was developed in 1943 by Warren McCulloch, a neurophysiologist, and Walter Pitts, a mathematician, 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 has been successfully applied to non-linear systems or systems with unclear dynamics. In particular, in contrast to mathematical models such as the regression model or proportional-integral-derivative (PID) controllers, ANN models have adaptability via a self-tuning process, so they can decide accurately without outside expert interventions when unusual perturbations, disturbances, and/or changes in building background conditions occur. Studies proved the advantage of ANN-based thermal control strategies over mathematical strategies [(Gouda, G. G., et al. (2006), Ruano, A. E., et al. (2006), DACS (2006), Loveday, D. L. (1992)).

1.3.1 Biological Approach of Neural Network

A human brain conducts information processing such as pattern recognition or data classification using past experiences. Those functions are executed in a series of neurons in a brain. This neuron consists of several components. “Dendrites” are a spread structure to contact and gain information from the surrounding. A “neuron” collects this information and sends out electrical activity through a long and thin strand called an “axon”, which is divided into thousands of branches. A “synapse” is located at the end of the axon and translates this electrical activity to electrical effects that control an activity in the next neurons. When a neuron takes electrical effects over an inherent threshold level, it sends out electrical activity to the axon for the next neuron. The next neuron conducts the same process for processing information. A learning process is executed by the change of effectiveness of the synapses resulting in the change of influence of one neuron on next neuron (Figures 1.3 and 1.4) [Stergiou, C., et al. (2006), DACS (2006)].



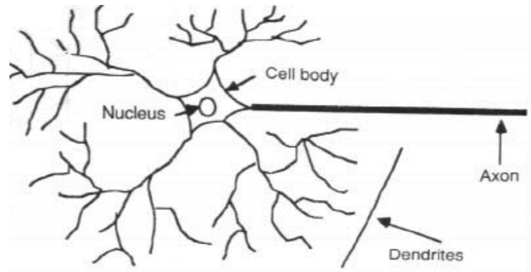


Figure 1.3 Component of Neuron

Figure 1.4 The Synapse [Stergiou, C. (2006)]

1.3.2 Engineering Approach of Neural Network

ANN is an engineering approach of the biological nervous systems, in which information processing is executed in way similar to the human brain. Thus, ANN employs similar components in its process.

1.3.2.1 Major Components

An ANN model is basically composed of three layers – input, hidden, and output layers. The input layer has neurons for obtaining a number of inputs. Each input value is multiplied by its own weight to be summed by the neurons in the hidden layer. The number of hidden layers and its neurons can be adjusted by the purpose of systems. Neurons in the hidden layer produce new values using a transfer function, and these new values are multiplied again by weights to output layers. Similar to the hidden layer neurons, output layer neurons also sum the values and make output, at this time, also using their transfer function (Figure 1.5).

ANN works based on the following six major components, which can be commonly applied to the neurons in input, output, or hidden layers [Stergiou, C., et al. (2006), DACS (2006)].

- Weighting Factors (connection weight, *w*): Neurons obtain many inputs simultaneously. Each input has its own weights with which the impact of input can be determined so that some input is regarded as more important than others. Weights are adaptive coefficients that can be modified by training sets and learning process.

- Summation Function (*NET*): There are various summation functions for manipulating and combining inputs such as minimum, maximum, majority, product, or several normalizing methods. The most simple and common summation method is to compute the weighted sum of all of the inputs. Inputs ($i_1, i_2, \ldots, i_n$) are multiplied by weights ($w_1, w_2, \ldots, w_n$), then added up as weighted sum ($i_1 * w_1 + i_2 * w_2 + \ldots + i_n * w_n$). This summed value is fed to the transfer function.
- Transfer Function (*TF*): The summation result (e.g. the weighted sum) is used in the transfer function for generating the output signal of each neuron. It has a threshold by which the summation result is determined. For example, when the sum is greater than the threshold, a neuron generates a signal. Or, it does not. Various transfer functions are used depending on the objectives, and the most general TF is the sigmoid function that has output ranges between 0 and 1.
- Output Function: With the exception of some network topologies, output (*o*) from many inputs is generally identical to the result of transfer function of the output neuron.
- Error Function and Back-Propagated Value: The current error is the difference between the current output and the desired output. This value is back propagated to a previous layer, and is used by learning function for changing weights before next cycle.
- Learning Function: A closer output to a desired output can be obtained after a learning process that is based on the learning function using error and back propagation. It is possible through the change of synaptic weights of each input.

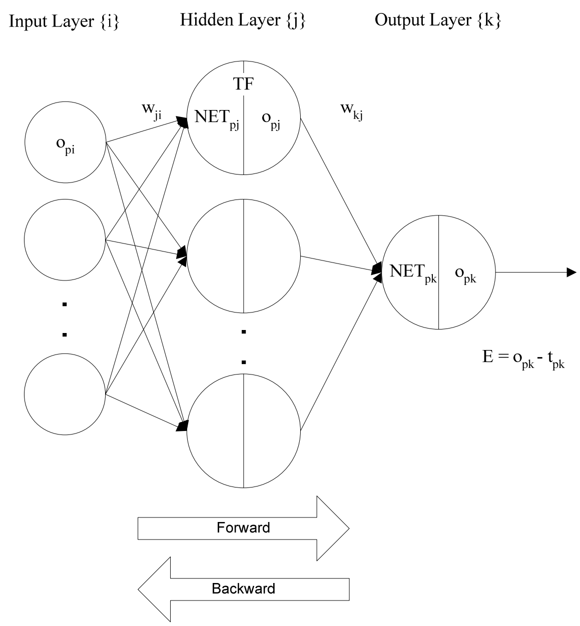


Figure 1.5 Architecture of Artificial Neural Network

1.3.2.2 Output Generating Process

Using multi-layers consisting of input, hidden, and output layers, an output generating process is conducted. This process begins at the input layer and ends at the output layer; thus it is called a feed-forward process. The detail of this process is given below [Yang, I. H., et al. (2003)].

Step 1: Input data are fed into the ANN model.
Step 2: Using connection weight w_{ji} between input and hidden layer, and an output o_{pi} of input layer node i, which is same with input data, NET_{pj} is calculated as an input value for hidden layer node j (Equation 1.10). P, here, represents the patterns of training data sets.

$$NET_{pj} = \sum_{i} w_{ji} o_{pi} \quad \text{(Equation 1.10)}$$

Where,
NET_{pj}: summation of weighted activations of all nodes in input layer

w_{ji}: connection weights between input and hidden layer

o_{pi}: output of input layer node i

p: patterns of training data sets

Step 3: Assuming the sigmoid function (Equation 1.11 and Figure 1.6) is applied as a transfer function in the hidden layer node, output o_{pj} of the hidden layer node j is calculated using Equation 1.12.

$$f(x) = \frac{1}{1+e^{(-x)}} \quad \text{(Equation 1.11)}$$

$$o_{pj} = f_j(NET_{pj}) \quad \text{(Equation 1.12)}$$

Where,

o_{pi}: output of hidden layer node j

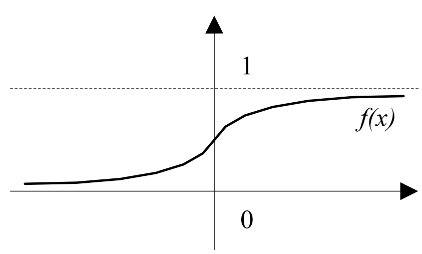


Figure 1.6 Logistic Sigmoid Function

Step 4: Using connection weight w_{kj} between hidden and output layer, and output o_{pj} of hidden layer node j, NET_{pk} is calculated as an input value for output layer node k (Equation 1.13).

$$NET_{pk} = \sum_j w_{kj} o_{pj} \quad \text{(Equation 1.13)}$$

Where,

NET_{pk}: summation of weighted activations of all nodes in hidden layer

w_{kj}: connection weights between hidden and output layer

Step 5: Assuming the sigmoid function (Equation 1.11 and Figure 1.6) is applied as a transfer function in the output layer node, output o_{pk} of the output layer node k is calculated using Equation 1.14. This value o_{pk} is the actual output calculated by the ANN model.

$$o_{pk} = f_k(NET_{pk}) \quad \text{(Equation 1.14)}$$

where,

o_{pk}: output of output neurons

1.3.2.3 Learning Process

Training, which is a synonym of learning by ANN model, is the process for modifying the weights of each connection for producing proper outputs from inputs. It uses training data sets that consist of matched input and output. Back propagation (BP) is the most popular learning algorithm for improving the accuracy of network models. It changes the connection weights for reducing the error. This process begins at the error in the output layer and continues to change weights between the input and hidden layer, so it is called a backward process. Detail is given below [Yang, I. H., et al. (2003)].

Steps 1: Error term for the output layer node is calculated using the difference between the desired output t_{pk} and the actual output o_{pk} (Equation 1.15).

$$\delta_{pk} = (t_{pk} - o_{pk})f_k^{'}(NET_{pk}) = (t_{pk} - o_{pk})o_{pk}(1 - o_{pk}) \quad \text{(Equation 1.15)}$$

where,

δ_{pk}: error term for connection weights between output and hidden layer

t_{pk}: desired output

Step 2: Error term for the hidden layer node is calculated (Equation 1.16).

$$\delta_{pj} = f_j^{'}(NET_{pj})\sum_k \delta_{pk}w_{kj} = o_{pj}(1 - o_{pj})\sum_k \delta_{pk}w_{kj} \quad \text{(Equation 1.16)}$$

Where,

δ_{pj}: error term for connection weights between hidden and input layer

Step 3: The connection weight between hidden layer and output layer is modified using Equations 1.17 and 1.18. Here, α is a learning rate and β is a momentum specified.

$$w(new)_{kj} = w(old)_{kj} + \alpha\delta_{pk}o_{pk} + \beta\Delta w(old)_{kj} \text{ .... (Equation 1.17)}$$

$$\Delta w(old) = w(old) - w(older) \text{ .... (Equation 1.18)}$$

Where,

α: a specified learning rate

β: a specified momentum

Step4: The connection weight between input layer and hidden layer is modified using Equations 1.19

$$w(new)_{ji} = w(old)_{ji} + \alpha\delta_{pj}o_{pj} + \beta\Delta w(old)_{ji} \text{ .... (Equation 1.19)}$$

Step 5: Repeat learning process for all learning data sets.

Step 6: Repeat learning process for the number of iteration (epoch) or until the goal is achieved.

1.3.2.4 Static and Adaptive Neural Network Models

There are two types of neural networks based on whether they can be modified or not [Yang, J., et al. (2005)]. A "static model" completes its learning process using historical data before application, and does not update the model parameters with the newly collected data afterward. Once the model is established, it produces output stably. However, the presence of new data, which has new information regarding model inputs and outputs, does not affect the network model.

On the other hand, an "adaptive model" continuously updates its parameters such as connections weights when new input and output data is available during the operation.

Through this process, the ANN model can respond properly to the change in environmental and operational background. Two adaptive models are proposed: the accumulative training and the sliding window training.

An ANN model using the accumulative training method is retrained by a set of augmented data when new information occurs; thus the size of the training data set increases. It is advantageous to generate stable output with fewer erroneous results. However, its disadvantages are reduced training speed and the smaller impact of newly added training data set.

The sliding window training method alternatively can be applied for improving these disadvantages. It uses a constant size of training data sets and the newest set is added to the training data sets replacing the oldest; thus the training speed does not increase. However, it could generate unstable output if the number of training data sets is not large enough.

1.3.3 ANN Applications to Buildings

Artificial-Neural-Network (ANN) increasingly has been applied for creating advanced building thermal conditions. Its application can be categorized in two groups: prediction and control. ANN models were designed to predict not only heating and cooling loads, but also energy consumption in buildings. In addition, they controlled the building environmental control devices such as heating and cooling systems. The following sections describe these current and previous studies investigating the ANN application to building environmental prediction and system control.

1.3.3.1 Prediction of Thermal Load and Energy Performance

a. Prediction of Heating and Cooling Loads

ANN has been applied to predict heating and cooling loads in buildings. Kalogirou, S. A., et al. utilized ANN for predicting the heating load of a building. A network model adapted building envelope data as inputs, which consisted of eight factors:

window area, external wall area, partition area, floor area, roof and ceiling code, window type code, wall type code, and design room temperature. The hidden layer had 10-neurons and the output was the heating load of the building. 225 training sets and 25 test sets were collected for learning and evaluating process, respectively. After the training process, the heating load by the network model showed an acceptable correlation coefficient with the actual heating load (e.g., 90 % of evaluating cases had less than 5% of error, and rest 10% of cases had 5~10% error); thus it indicated that this method using ANN could be successfully applied to heating load estimation for other buildings [Kalogirou, S. A., et al. (1996)].

ANN has been applied for the prediction of cooling load as well. Shin, K. W., et al. developed an ANN-based strategy for operating an ice storage system. They employed a current day's temperature and humidity for calculating the next day's temperature and humidity using mathematical equations. These calculated temperature and humidity values, as well as the historical data for the past cooling load, were fed into the ANN model as inputs for predicting the next day's cooling load. This predicted cooling load was utilized for the operation of the ice storage system. In conclusion, the operation of an ice storage system using ANN was acceptable except on rainy days when significant errors occurred during calculation of temperature and humidity using equations, and prediction of cooling load using ANN model [Shin, K. W, et al. (2003)].

In addition, ANN was applied for predicting both heating and cooling loads. For ANN training and testing, a DOE 2.1D energy simulation tool calculated the heating and cooling loads of buildings that had different characteristics in architectural elements and building operating conditions. ANN had ten input neurons such as internal load by lighting, internal load by equipment, ceiling height, fenestration ratio, overhang coefficient, daylight, thickness of insulation, thickness of roof insulation, glass conductance, and shading coefficient. These inputs were utilized for calculating outputs: heating and cooling loads. Simulated 256 sets and other 5 sets using the DOE tool were used as training sets and test sets, respectively. The performance test indicated that the ANN outputs traced well to the simulation outputs, thus the ANN-based prediction of the heating and cooling load showed potential to be applied to actual buildings with the advantage of easy application [Kim, S. H., et al (2000)].

b. Prediction of Energy Consumption

Datta, D., et al. investigated the ANN application for the prediction of energy consumption in a supermarket. In this study, they modeled seven different neural network models that had different sets of inputs for the purpose of finding out the impact of each input factor. Diverse combinations of parameters were used as input sets: day, time, external humidity of a month, external temperature of a month, internal humidity of a month, internal temperature of a month, external humidity for four months, external temperature of four month, and time-series prediction using past six time steps. The output of network was the electrical energy consumption. In addition, actual data in the subject building were used for training and testing network models. Through comparisons between the predicted energy consumption using ANN and the actual data, the proposed ANN based method showed reasonable accuracy with correlation coefficients ranging from 0.91 to 0.95, which were much improved values compared to those of the multiple linear regression models (ranging from 0.49 to 0.75). In addition, it found that the most significant factor for predicting the electricity consumption was the time of the day [Datta, D., et al (1997)].

A similar study was conducted using a neural network for a passive solar building. ANN was utilized for the prediction of energy consumption (electricity) in winter and summer based on the inputs with season, insulation, wall thickness, function (whether the heat transfer coefficient is variable or constant), and time of the day. Training and testing sets were collected using a DOE simulation tool. As a result of the analysis, the actual amount and the predicted amount of electricity consumption had a close relationship of $R^2 = 0.9991$. Thus, based on the accuracy of prediction as well as the ease of design and use, the ANN model had the potential to successfully predict energy consumption for a passive solar house [Kalogirou, S. A., et al. (2000)].

Kreider, J. F., et al. tested a neural network model for predicting the compressor power and electric consumption of an HVAC system in a commercial building. In this research, a traditional regressive model such as SVD (Singular Valued Decomposition) was compared with an ANN-based model. The ANN model in this study employed building occupancy, as well as sine and cosine of the hour number to roughly represent the diurnal change of temperature and insolation, wind speed, ambient relative humidity, ambient dry bulb temperature, previous hour's ambient dry bulb temperature, two hour's previous ambient temperature, and previous hour's electrical power consumption as inputs for predicting the compressor power and energy consumption. Analysis showed the advantages of the ANN model over the regressive model were that the ANN model was more accurate than the regressive model and did not require expert knowledge for design and use. Thus, ANN could be an advanced solution for predicting compressor power and energy consumption of HVAC systems [Kreider, J. F., and et al. (1992)]. Similarly, an ANN model was developed for predicting electric energy consumption by González, P. A., et al. Inputs consisted of current temperature, forecasted temperature, current load, current load, the hour, and the day. Analysis revealed the excellent results for electric load forecasting in buildings using ANN model [González, P. A., et al. (2005)].

Aydnalp, K. M., et al. compared the performance of three methods for end-use energy consumption of residential buildings: an engineering method, neural network, and a CDA (Condition Demand Analysis). An engineering method employed a computer simulation tool for calculating energy consumption. A CDA, which is a type of a regression equation, used diverse environmental parameters (e.g., efficiency of systems, glazing types, number of occupants, etc) and their impacts on energy consumption. According to the comparisons of a performance test, the neural-network-based method most accurately predicted the energy consumption for ALC (appliance, lighting, and space cooling), DHW (Domestic Hot Water), and space heating. It showed the highest R^2 (multiple correlation coefficient) and the lowest CV (coefficient of variation) with the actual energy consumption data. In addition, the neural network model could most flexibly consider the socio-economic factors (e.g., household income, dwelling type and ownership, number of children and adults, and size of area of residence) for predicting energy consumption. Thus, authors suggested a neural network model as an energy prediction method considering socio-economic factors [Aydinalp, K. M., et al. (2007), (2004), and (2002)].

c. Optimal ANN Structure for Predicting Energy Consumption

Regarding to the structure of ANN models, Mihalakakou, G., et al. compared two adaptive training methods for an ANN model that was aimed at predicting heating and cooling energy in a one-story detached residential building. The first method employed an ANN model that had the measured ambient air temperature and total solar radiation of an hour as inputs, and the energy consumption as an output. On the other hand, the second method employed three ANN models: one primary model was for predicting energy consumption, and the other two models predicted ambient air temperature and total solar radiation, which were used as inputs of the primary model. Therefore, the difference of these two methods was the type of inputs – measured data or predicted data. The predicting accuracy of these two methods was investigated using the actual measurement data of the past years. The first method, which employed measured data for inputs, predicted the amount of energy consumption close to the actual consumption. Its correlation coefficients were 0.96 for cooling energy in summer and 0.94 for heating energy in winter. In addition, the second method, which used predicted data for inputs, also showed sufficiently accurate results, so that 90% of predicted hour-by-hour energy consumption fell between -8 and 15% difference with actual energy consumption. Based on the analysis, this study proved the applicability of ANN models for predicting energy consumption in residential buildings [Mihalakakou, G., et al. (2002)].

The other approach for an optimal design of ANN model was conducted by Karatasou, S. et al. They studied the relevance of environmental parameters for predicting the energy consumption of commercial buildings. In the study, they found the importance of ambient temperature, solar radiation, the day and time variables, and occupancy status as inputs of ANN model along with the insignificance of wind speed and ambient humidity. In addition, the 1-step predictor was proven as the optimal method for predicting energy consumption. At the same time, for the prediction of daily energy consumption, an independent ANN model was better than an iterative approach of 1-step predictor [Karatasou, S., et al. (2006)].

Yang, J., et al. employed an adaptive artificial neural network that was flexibly applied to different buildings. It could overcome the significant limitation of the traditional ANN method that could not be applied to buildings having different characters because the network model was trained and fixed to be suitable to a typical building setting. On the other hand, the adaptive network model could update the model parameters (e.g., connection weights) through a continuous training process using new data collected from a new setting. Both accumulative training and sliding window training methods, which are two primary methods for adaptive training, were evaluated in term of accuracy. Analysis revealed that the ANN model using the sliding window training method predicted the amount of energy consumption for a chiller more closely to the actual data than did the accumulative training method. Thus, the adaptive neural network model using sliding window training could be applied as an advanced method for the prediction of cooling energy in buildings [Yang, J., et al (2005a), (2005b)].

1.3.3.2 Control of Building Thermal Conditions

a. Control of Heating Systems

ANN models were applied to determine optimal start and stop times for heating systems. Yang, I. H., et al studied the optimal start time of the heating system for office buildings. During the nighttime in the building (e.g., office buildings) when it is unoccupied, a setback mode for a heating system is applied for reducing the energy consumption in winter. And, as it becomes closer to the business hour in the morning, it returns to the normal mode for supplying comfortable thermal conditions to the occupants. At this moment, if the starting time of the heating system for restoring the interior temperature to the comfortable level is too late, occupants feel cold for a while in the initial time of the day. In the reverse condition that the start time is too early, unnecessary energy is consumed for the time of vacancy. An ANN model was suggested for preventing these improper operations, with which the optimal start time for a heating system could be predicted. Room air temperature, changing rate of room air temperature, outdoor air temperature, and changing rate of outdoor air temperature were chosen as inputs of a network model, and the time required to reach the desired temperature after heating begins was selected as the output of a network model. Training and test sets were obtained from the actual building. Test results showed that the predicted time using the ANN model had a close correlation coefficient to the results from the actual building. Thus, the ANN model for predicting the optimal start time proved to have the potential to optimally start heating systems in office buildings [Yang, I. H., et al (2003)].

An ANN model having similar structural model but generating the opposite output result was studied. This model predicted the time required for descending current air temperature to the lower limit of the specified comfort range. For making this prediction, it employed the same inputs as the previous study: room air temperature, changing rate of room air temperature, outdoor air temperature, and the changing rate of outdoor air temperature. Using this predicted time value, a heating system could predetermine its restarting moment. Thus, indoor air temperature could be stabilized better within the specified comfort range [Yang, I. H., et al. (2004)].

Lee, J. Y., at al. developed s similar ANN model for operating a radiant heating system embedded under the floor. It utilized the same inputs as the previously studied model (Figure 1.7). It produced two outputs: maximum value of room temperature increase and maximum value of room temperature decrease. When a radiant heating system is working, the network model predicts the maximum value of room temperature increase after the currently working heating system is turned off. If this predicted value plus current room temperature is higher than the upper limit of the specified comfort range, the heating system is immediately turned off. On the other hand, when a heating system is not working, the network model predicts the maximum value of room temperature decrease after currently non-working heating system is turned on. If this predicted value plus current room temperature is lower than the lower limit of the specified comfort range, the heating system is turned on. Using this predetermined operations of the heating system, overshoot and undershoot were significantly reduced [Lee, J. Y, et al. (2002, 2000, 1999, and 1998)].

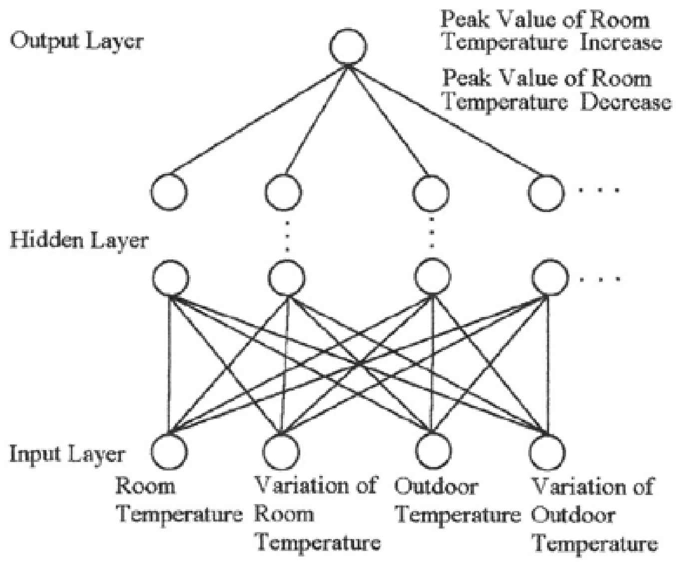


Figure 1.7 The ANN Model for the Predictive Control of the Radiant Floor Heating System

Morel, N., et al. employed ANN models for controlling a similar heating system in residential buildings. Three neural network models were developed. The first two models were for the prediction of the external temperature and solar radiation. And, the last model was for predicting the building thermal behavior. Specifically, the last ANN model used the outputs of the first two models as inputs in conjunction with the current inside temperature, previous inside temperature, internal gain, and heating equipment gains. Based on these inputs, it predicted the future value of inside air temperature. This predicted value was used for optimal control of the radiant water heating system. Analysis revealed that thermal comfort and energy efficiency were advanced using these ANN models [Morel, N., et al. (2001)].

Argiriou, A. A., et al. tested a similar network model for hydronic heating systems of solar buildings to predict an optimized heating supply based on the forecasted outdoor air temperature, solar irradiance, heating supply temperature, and indoor air temperature. The performance of the ANN-based control and the PID control was tested using experiments and simulations, and the results were compared. The comparison indicated that the ANN method significantly reduced energy consumption by 15% compared to the conventional controller [Argiriou, A. A., et al. (2004 and 2000)].

Cooperation of ANN with another AI (artificial intelligence) method was studied for the optimal control of a heating system. Gouda, M. M., et al. developed a controller using ANN and Fuzzy logic together. The purpose of the ANN model was to predict the indoor air temperature as an output. This predicted indoor air temperature and its difference from the desired setpoint temperature were used as inputs for the Fuzzy controller. Based on these two inputs, the Fuzzy controller determined the operation of a heating system. The performance of this quasi-adaptive Fuzzy controller was compared with that of the conventional PI (proportional and integral) controller. Reductions of overshoot (overheating) and energy consumption were remarkably achieved using the proposed ANN-Fuzzy controller [Gouda, M. M., et al., (2006)].

b. Control of Cooling Systems

The prediction of the optimal end of setback time for a cooling system was studied using an ANN model. Ben-Nakhi, A. E., et al. developed an ANN model for predicting the time of the end of thermostat setback for restoring the interior temperature in time for the start of the business hours. Exterior air temperature was the only input factor of the model. This developed model was trained using the simulated data from ESP-r. In the performance test, the prediction by an ANN model showed a strong correlation coefficient with the simulated result. In addition, the ANN model required much simpler input than did the simulation tool. Thus, the ANN-based predictive control for a cooling system proved its potential for accuracy and ease of use [Ben-Nakhi, A. E., et al. (2002)].

Abbassi, A., et al. developed an ANN model for operating an evaporative condenser and compared its performance with a PID controller. As inputs, refrigerant condensing temperature, refrigerant mass flow rate, inlet air temperature, inlet specific humidity, and water mass flow rate were employed for predicting the evaporated water mass flow rate, condenser cooling load, and outlet temperature and specific humidity outputs. Analysis revealed that the predicted cooling load (i.e., the cooling effect) using the network model was similar to that of the actual condenser. In addition, the performance of the ANN-based method proved to reduce the process errors compared to those of the PID controller. At the same time, the model generation using ANN was much simpler than that using the PID control method [Abbassi, A., et al. (2005)].

A similar project was conducted for the optimal use of energy (fuel and electricity) for operating an absorption chiller system. It integrated ANN and GA (genetic algorithm) in achieving the minimization of operating cost. A neural network consisted of 4-layers for network: one input layer, two hidden layers, and one output layer. It employed inputs with set point temperature of chilled water supply, chilled water flow rate, cooling water flow rate, return cooling water temperature, and cooling tower fan operation while outputs with mass flow rate of diesel oil (M_{fuel}), respective electric power of the cooling water pump (P_{cool}), chilled water pump (P_{chill}), and COP. Outputs from the ANN model were fed into GA (Genetic Algorithm), which used a cost function and an iterative evaluation process for optimizing chiller operation based on the operating cost. Analysis indicated that the performance of ANN model for predicting M_{fuel}, P_{cool}, P_{chill}, and COP was successful with reasonable accuracy. Correlation coefficient R, which is acceptable if it is less than 0.1, of each output was 0.0564, 0.0804, 0.0724, and 0.0494, respectively (Equation 1.20) [Chow, T. T., et al. (2001)].

$$R = \frac{1}{|\bar{a}|}\sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - a_i)^2} \quad \text{(Equation 1.20)}$$

where,

R: correlation coefficient

t: target output

a: actual output

n: number of outputs

$\bar{a}$: mean of all actual outputs

Ruano, A. E., et al. developed and compared two different neural networks for controlling an air conditioner based on the prediction of indoor temperature. The first one was a fixed network that employed inside air temperature, outside solar radiation, outside air temperature, and outside relative humidity as inputs for predicting expected indoor temperature as output. The second model was an adaptive network with a sliding window method that had the same inputs with a fixed network. The result revealed that the adaptive network model more accurately predicted the future indoor temperature. Thus, a cooling system controlled by the adaptive network stabilized the indoor air temperature better within the specified comfort range and advanced the energy efficiency compared to that controlled by the fixed model or state-of-the-art physical models [Ruano, A. E., et al. (2006)].

1.4 Summary

The indoor environmental quality (IEQ) of residential buildings, which describes the environmental conditions of interior—physical, psychological, and sociological conditions, is deeply associated with occupant comfort, health, and productivity at home. Its significance is increasingly recognized with the increase of the spending time at home.

Thermal performance in residential buildings, which is one of the significant factors determining the IEQ, presents problems yet to be addressed. The first problem is thermal imbalance due to the limited number of thermal zones and thermostat applications. In addition, thermal discomfort occurs due to the overshoots and undershoots caused by the time-lag of the control systems and the building thermal response. At the same time, limited types of thermal factors are currently considered to be controlled (e.g., air temperature is generally the only target while humidity is rarely controlled and the PMV is not counted to be controlled). These thermal issues will be addressed again when the objectives of the study is described.

Models for describing thermal comfort are classified into two categories—static and adaptive. In the static models, human are assumed as passive subjects who do not do any efforts to change the environment, so that the thermal comfort range is constant. On the contrary, in the adaptive models, humans try to adapt themselves to the new environment through behavioral, physiological, and psychological adaptation as active subjects. Thermal sensation (TS) models, predicted mean vote (PMV), and two node models were examples of the static models while the adaptive indoor comfort temperature and the adaptive neutral temperature are those of the adaptive models.

An artificial neural network, which is an analogous to the human brain and its learning process, is increasingly applied in building thermal control. Based on its superiority of prediction and adaptation, ANN models have been successfully employed for predicting heating and cooling loads as well as energy consumption for heating and cooling in buildings. In addition, diverse network models have been developed for controlling building environmental control systems such as heating and cooling systems based on the predicted thermal conditions (e.g., forecasted climate conditions or indoor air temperature). The performance tests were comparatively conducted with those of the conventional models such as regression models or PID (proportional-integral-derivative) controllers. Analysis revealed that the ANN-based control strategies were more accurate for predicting loads, energy consumption, and thermal conditions. In addition, they not only controlled indoor thermal conditions better within the specified comfort ranges, but also improved energy efficiency when they were applied to the operation of building control systems. In particular, in contrast to mathematical models such as the regression model or PID controllers, ANN models have adaptability via a self-tuning process, so they could perform more accurately than did fixed models when changes in building background conditions occurred.

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CHAPTER II

TRENDS IN RESIDENTIAL BUILDING THERMAL CONTROL

Historically, the 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, K. C. (2003)]. In addition, as energy costs increase significantly, so, too, home energy efficiency acquires economic importance. Simultaneously, the emergence of the home office concept has caused productivity to become an important economic factor [Harper, R. (2003)]. Accordingly, new residential buildings demand advanced climatic control strategies providing comfort, health, productivity, and energy efficiency.

2.1 Trends in Conventional Thermal Control in Residential Buildings

Trends of conventional building thermal control strategies can be summarized in three features: independent, static, and inflexible (Figure 2.1).

2.1.1 Independent Control

In the conventional buildings, environmental factors influencing environmental quality have been controlled independently. For example, systems and strategies for thermal control, lighting control, security and access control have not been designed for interoperable operations. Thus, the optimized environmental control method could not be applied [Boyd, D. (1994)]. Even for the control of a single environmental factor such as thermal quality, diverse equipments and appliances (i.e., HVAC, heater, A/C, humidifier, dehumidifier, etc) have worked independently without an optimized control logic. In this circumstance, temperature and humidity were conditioned separately, resulting in frequent thermal discomfort as shown by measures such as thermal sensation (TS) or predicted mean vote (PMV). This independent control could cause energy inefficiency as well. For example, in summer, generally specified comfort ranges for air temperature (23~26°C) and humidity (30~60%) from standard such as ASHRAE are lower than for the PMV (-0.5~0.5) (e.g., when air temperature is 23°C and humidity is 30%, PMV is -1.27 with an assumption that the MRT is same with air temperature, 0.0m/s air velocity, 0.5CLO, and 1.0MET) [ASHRAE (1997) and (1992)]. Thus, independent air temperature and humidity control method could consume more energy for cooling down space than could the PMV-based control logic.

2.1.2 Static Control

Conventional control strategies and system components have employed limited environmental information (e.g., current interior temperature and humidity for thermal control). However, they have not taken dynamically changing environmental factors (e.g., exterior thermal conditions, variance of interior and exterior thermal conditions, occupancy status, etc.) and the building's thermal response to system operations into account. With such static control, control methods were not able to respond dynamically changing environmental conditions. As results, thermal discomfort and energy inefficiency could occur. In addition, user comfort-based control methods were not implemented in most buildings. Since user interaction to the environmental control process was rarely possible, occupant comfort needs could not be met properly.

2.1.3 Inflexible Control

The thermal environment in residential buildings has usually been conditioned using a limited number of thermostats (e.g., control whole building by one thermostat located in the living room). On the other hand, a control method flexibly accessed by multi-users from different locations, which employs several control panels distributed in different spaces, has not been introduced in most residential buildings. Thus, the advanced control methods such as localized controls and remote controls of environmental systems were not flexibly applied. Therefore, sophisticated functions for satisfying diverse occupant needs were difficult to be fulfilled.

2.2 Trends in New Thermal Control in Residential Buildings

Building control systems are getting smarter. Technology is embedded and hidden in the background, so that occupants do not need to explicitly recognize the existence of a control system. Instead, systems are sensitive, adaptive, and responsive to the presence of people. Components are smaller, lower-power, lower-weight, and lower cost, yet they can collaborate or interact with each other with interoperable and open protocols. New technology supports the advanced control strategies in terms of integrated, dynamic, and flexible control (Figure 2.1).

2.2.1 Integrated Control

Integration in control system is the ability to coordinate and utilize different technologies together such as sensing, control and monitoring systems, and actuators. Interoperable system components with the same protocols, standard protocols, and open systems in network space are necessary for communication in the integrated system [McGowan, J. J. (1992), Atkin. B. (1988)]. In addition, integrated control logic is required for the optimized control of thermal and air quality, lighting, fire alarm, security, access control, lifting, etc. Also, for the control of single environmental factors such as thermal quality, diverse equipments and appliances (e.g., HVAC, heater, A/C, humidifier, dehumidifier, etc) will be considered together based on the optimized control logic. For example, diverse environmental control components (e.g., sensors, data acquisition systems, actuators) can be integrated and work interactively based on the integrated control logics not only for conditioning temperature and humidity independently, but also for maintaining the overall thermal comfort (TS or PMV) and for improving energy efficiency.

2.2.2 Dynamic Control

A dynamic control method draws diverse factors relative to buildings in the control process. First, it utilizes diverse environmental factors as controllers. Control logic responds effectively to changing environment conditions such as a variance of exterior thermal conditions, thermal response of the building, system performance, occupancy patterns, etc. Second, it employs individual occupants as controllers. Occupants are able to interact with the system through a user interface. Using this user satisfied integrated control strategy, user satisfaction and productivity can be increased [Atkin, B. (1994)]. Under this circumstance using environmental factors and individual occupants as controllers, advanced thermal control strategies such as unoccupied period control, optimal start-stop control (adaptive energy-saving program), zero-energy band program, enthalpy program, etc, are feasible [Carson, R. A., et al. (1991)].

2.2.3 Flexible Control

Newly applied environmental control systems are moving from a centralized control and monitoring system to a PC-based system operator interface (SOI). Occupants can flexibly reflect their requirements using the PC-based interface in a network space, so that the highly sophisticated functions can be determined by individual occupants.

In addition, micro-processors-attached intelligent small devices are developed for manipulating environmental information by themselves and for performing control functions independently. Thus, it is unnecessary to follow signals from a control panel [CIBSE Guide H (2000)]. The intelligent sensor is one example that adopts not only sensing elements, but also on-board micro chips. These sensors can translate analog signals to digital signals by themselves. Using these digitalized signals, mathematical manipulations can be conducted on the sensor board (e.g., enthalpy calculation from sensed temperature and humidity). This capability simplifies the data manipulation process and reduces performance load in the control panel [Atkin, B. (1994)].

At the same time, control strategy using wireless technology is just beginning to be introduced. The wireless sensor is an example applied in thermal control. By flexible using the increased numbers and types of wireless sensors in space, a highly distributed control system can be realized, through which occupants can be actively involved in control loops for individualized control [Weber, W., et al. (2005)].

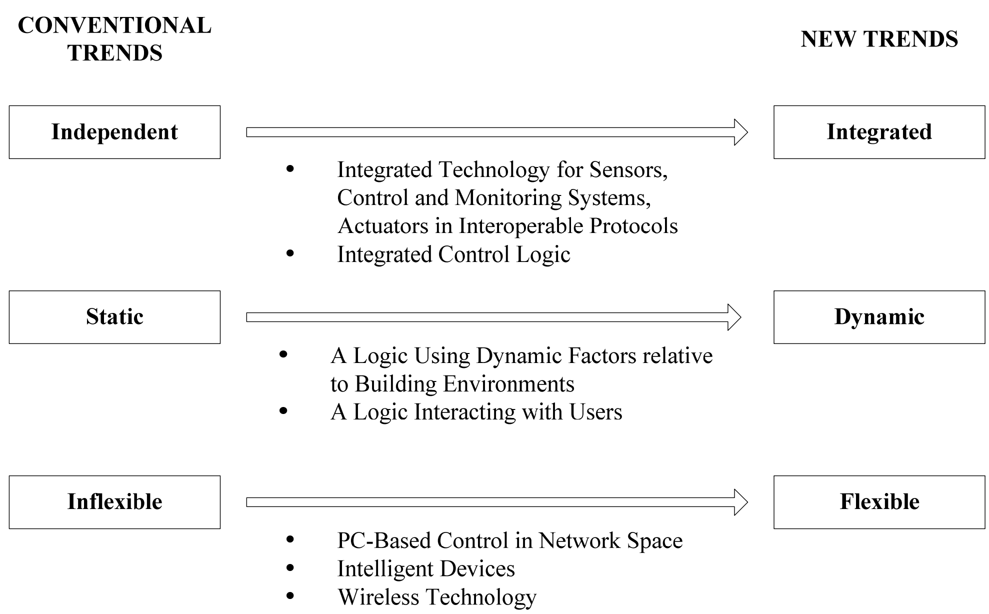

Figure 2.1 Movement from the Conventional Trends to the New Trends in Residential Building Thermal Control

2.4 Summary

Application of thermal control systems to the conventional residential buildings has been simplistic, in which the thermostat has been employed as the principal control system. Conventional building control is independent, static, and inflexible. No optimized control logic was developed for the operation of home climate control devices. In addition, only limited environmental information was taken into account in the control logic. User interaction to the control logic was limited.

On the contrary, new building control strategies are integrated, dynamic, and flexible. System components such as sensors, data acquisition systems, control panel, and thermal control devices work in interoperable open systems while logic integrates information for controlling thermal conditions including not only indoor air temperature but also humidity and Predicted Mean Vote (PMV). In addition, thermal control logic employs dynamic environment and occupant factors in a control algorithm. Moreover, by application of personal computers (PC) with communication technologies as well as intelligent and wireless devices, occupants are able to access the control process flexibly. Localized demand and control can be utilized to improve thermal quality. Thus, these new trends in thermal control were actively taken into account when the control logic and hardware framework were developed in this study.

Notes to Chapter II

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CHAPTER III

RESEARCH SCOPE

3.1 Problems

Conventionally, domestic thermal conditions are controlled by independent control system devices (e.g., hot air or water system, air conditioner, etc) that work based on the thermostat. Under this simplistic method, thermal discomfort frequently occurs due to an improper operation of system devices, and this causes the unnecessary energy consumption as well. The problems with residential thermal control method that causes these phenomena are (1) lack of the advanced thermal control logic, and (2) lack of the integrated control system. Moreover, (3) existing ANN models, which aim to improve the thermal conditions and energy efficiency, have limitations as well.

3.1.1 Lack of the Advanced Thermal Control Logic

Current simplistic control methods for residential buildings are lacking logic for optimal control of thermal conditions. First, current control logic is a static method that considers only the current interior air temperature and, sometimes humidity for deciding system operations. Other diverse thermal factors such as interior PMV, exterior thermal conditions, variance of interior and exterior thermal conditions, and occupancy are not taken into account in determining system operations. With such static controls, thermal discomfort and waste of energy can take place frequently. For example, when exterior air temperature is rising in the morning of a heating season, interior air temperature also begins to rise. Under this condition, interior thermal conditions can be comfortable without operations of a heating device. However, current control methods, which do not consider the variance of exterior and interior air temperature, will decide operation of the heating device just based on the current interior air temperature. Thus, this unnecessary operation of a heating device can cause the space to be overheated and energy to be wasted. In addition, in most residential buildings, humidity and PMV are rarely or never considered as a control variable. Thus, even in a comfortable space in terms of air temperature, occupants may feel uncomfortable humidity conditions (e.g., dryness or dampness) or PMV conditions (e.g., out of comfort range between -0.5 and 0.5).

Moreover, current thermal control methods for residential buildings do not take into account the time lag effect, which is the time difference between the system operation and the actual effect to the space, when system operation is decided. This can cause the overshoot or undershoot of thermal comfort factors. For example, a heating device stops working when the interior air temperature goes higher over the upper limit of a specified comfort range (e.g., 23°C in winter). Interior air temperature, however, does not drop immediately. Instead, it still rises due to accumulated heat in the heating device such as a radiant water heating system. This overshoot causes the uncomfortable thermal conditions. Therefore, a predetermination of system operation needs to be considered.

3.1.2 Lack of the Integrated Control System

Thermal control devices in current residential buildings work independently without integration. Devices for temperature control and humidity control follow signals from a thermostat and a hygrometer, respectively. No cooperation between two devices exists. Under this situation, even though each thermal factor satisfies its comfort range individually, overall thermal comfort (e.g., PMV) is apt to be uncomfortable. For example, even when the interior air temperature and humidity are within comfort ranges with 20°C and 30% in winter, the combined comfort level can be below the comfort range (-0.5~0.5).

In addition, thermal conditions in current residential buildings are dependent upon the limited number of devices for collecting thermal data and deciding system operation. In general, a thermostat in a living room is in charge of conditioning the whole space. This causes a thermal imbalance in space. Therefore, a control panel network consisting of multiple sensors needs to be distributed in space under an integrated system framework for the sensitive thermal control satisfying user specified requirements.

3.1.3 Limitations of Existing ANN Models

As presented in Chapter 1.3 "Artificial Neural Network (ANN) in Building Thermal Control," previous studies using ANN models for building thermal control proved that the ANN-based control methods improved thermal conditions using predictive methods compared to the conventional control methods such as the regression model and PID controller. Those studies, however, regarded indoor air temperature as the only control variable, while other important thermal factors such as humidity and PMV were not considered. Therefore, it is beneficial to develop ANN models that are capable of regulating building thermal systems based on factors indicative of thermal comfort including humidity and PMV.

In addition, the adaptability of existing ANN models has not been thoroughly tested. They used limited cases for testing, thus the self-tuning process has yet to be proved. Therefore, performance tests need to be conducted for changing building conditions and disturbances that buildings may experience during their life-span.

3.2 Research Objectives

This research aimed to develop an ANN-based advanced residential thermal control method for providing more comfortable thermal conditions in terms of air temperature, humidity or PMV, and to investigate their energy efficiency. A thermal control logic framework and a system hardware framework were proposed as the advanced residential thermal control method. In addition, this proposed method is a potential framework for the future expanded environmental control method using expanded control logic (e.g., thermal and air quality control logic) and expanded systems (e.g., multi-zone control with distributed sensor and control logic network).

A thermal control logic framework consisted of five steps for controlling thermal conditions: physical condition, thermal comfort range, energy, decision of system operation, and operation of control devices. In particular, four control logics were developed, which were employed in the decision of system operation. Those were a conventional logic: temperature and humidity control without ANNs; and three proposed logics: (1) temperature and humidity control with ANNs, (2) PMV control without ANN, and (3) PMV control with ANN.

- Temperature and humidity control without ANNs: This was the commonly applied conventional control logic in residential buildings. It employed indoor air temperature and humidity as control variables. This control logic decided the operation of the climate control devices based on information from a thermostat (air temperature sensor) and hygrometer (humidity sensor). Independent signals were produced for operating air temperature and humidity control devices.
- PMV control without ANN: This was the first proposed logic. It employed interior PMV as a control variable. Based on the current interior PMV level, logic decided the operation of control devices. For example, when the current PMV was lower than the specified comfort range (e.g., -0.5~0.0 in winter), logic produced signals for turning on devices (e.g., heater and humidifier) for increasing PMV.
- Temperature and humidity control with ANNs: This was the second proposed control logic. Different with the conventional logic, this logic employed two ANN models for predictively determining a maximum amount of temperature and humidity rise or drop when the current operating mode of control devices (e.g., heater and humidifier) is changed. Using the predicted thermal conditions, control logic could predetermine device operations. For example, an ANN model predicted ΔTemperature which was the maximum rise of temperature after stopping the currently working heating device. Logic summed ΔTemperature and current air temperature, and compared this value with the upper limit of comfort range (e.g., 23°C in winter). If the summed value was larger than the upper limit of comfort range, a heating device would be turned off before air temperature reached the upper limit of the comfort

range. By this predetermined operation, discomfort of indoor air temperature out of comfort range could decrease.

- PMV control with ANN: This was the third proposed logic. Similar to the Temperature and humidity control with ANNs, it employed ANN model for predicting ΔPMV. Using the predicted ΔPMV and current PMV, control logic could predetermine device operations for reducing thermal discomfort.

A system hardware framework was developed for the optimal thermal control through the integrated information on climate conditions and the coordinated device operation. It consisted of several technical components: sensors, data acquisition system, control panel (computer hardware and control logic), and climate control devices. Six thermal quality parameters, which were exterior air temperature and humidity, interior air temperature, humidity, MRT, and air velocity, were monitored and transferred to the control panel through data acquisition system. Using transferred data, developed control logic produces output signals for operating climate control devices. Based on the signal from control logic, climate control devices worked for improving the interior thermal conditions.

The proposed control method satisfies the new trends of building thermal control (integrated, dynamic, flexible), and employs predictive and adaptive (model-free) control strategies.

- Integrated control: Proposed logic took diverse thermal factors (e.g., air temperature, humidity, MRT, air velocity, CLO, and MET) into account together for conditioning the thermal quality in terms of not only air temperature, but also humidity or PMV. Using these data, logic produced signals for operating control devices in an integrated manner. For these, the proposed hardware framework integrated independent components (e.g., sensors, data acquisition systems, and independent climate control devices) using DDC (Direct Digital Control) technology.
- Dynamic control: Proposed logic employed dynamically changing thermal factors (e.g., exterior thermal conditions, variance of interior and exterior thermal conditions) in determining systems operation. In addition, it was a

user-satisfied control method that allowed user interaction in a decision process utilizing their thermal preference and system setback mode. The proposed hardware framework supported dynamic control using a sensor network for monitoring and transferring diverse thermal information.

- Flexible control: Proposed logic and hardware framework were designed being applied in PC environment. Thus, this proposed method can expand for more sensitive control with localized demand and control using communication technology. For example, using network communication, multi users' interaction in multi locations will be feasible in the future expanded system.
- Predictive control: ANN models were employed for predicting Δair temperature, Δhumidity, and ΔPMV of interior. These predicted values and the current values were used together for deciding device operations in the algorithm. Thus, the control devices worked for more comfortable thermal conditions based on the predetermined signals from ANN-based control logic.
- Adaptive (model-free) control: ANN models employed a sliding window method for updating their training data sets. The connection weights in the network models were continually modified using these updated sets. By this process, ANN models maintained their conditions with the newest information.

The performance of the proposed control method was tested for a change of building conditions (architectural variables: change of orientation, envelope insulation, and window-wall-ratio) and for disturbances that buildings may experience during their life-span (architectural variables: internal load and ventilation, systematic variables: change of setback and setpoint, and exterior climatic variables: extreme change of exterior thermal conditions).

3.3 Hypothesis

The hypothesis was concerned with (1) thermal comfort, (2) features of overshoots and undershoots out of the specified comfort ranges, and (3) energy efficiency.

3.3.1 Thermal Comfort

The performance of four developed logics (one conventional and three proposed logics) for creating thermal comfort was hypothesized that

- Conventional logic (temperature and humidity control without ANNs) was expected to create thermal discomfort, which would have a lower percentage of comfort period. Interior air would be over-heated, over-cooled, over-humidified, or over-dehumidified. It is due to the time lag effect.
- Two proposed logics using ANN models (temperature and humidity control with ANNs, and PMV control with ANN), were expected to provide the more comfortable thermal conditions in terms of air temperature and humidity, or PMV. Thus, the percentage of comfort period would increase. This is due to the predictive control of the devices which uses predetermined operating signals from ANN-based logic.
- Two proposed logics having PMV as the control variable (PMV control without ANN, and PMV control with ANN) would create a more comfortable PMV condition than would the other logics having temperature and humidity as control variables. This is due to the difference of each specified comfort range for air temperature, humidity, and PMV. The comfort ranges for the PMV (-0.5~0.0 in winter and 0.0~0.5 in summer) is higher than those of air temperature (20~23°C in winter and 23~26°C in summer) and humidity (30~45% in winter and 45~60% in summer). Thus, the percentage of comfortable period in terms of PMV is higher by logic having PMV as the control variable.

3.3.2 Features of Overshoots and Undershoots out of the Specified Comfort Ranges

Features of overshoots and undershoots out of the specified comfort ranges by developed logics were hypothesized that

- Two logics without ANN models (conventional logic: temperature and humidity control without ANNs, and one proposed logic: PMV control without ANN) would produce significant amounts of ratio and magnitude of overshoots and undershoots out of the specified comfort ranges.

- On the contrary, two proposed logics using ANN models would reduce those values because they predetermined the system operation using predicted thermal conditions by ANN.

3.3.3 Energy Efficiency

Energy efficiency by developed logics, which was determined by the amount of heat supply and removal, and moisture supply and removal for the simulation results while the amount of electricity for heating, cooling, humidifying, and dehumidifying for experimental results, was hypothesized that

- Two proposed logics using ANN models, were expected to be more energy efficient compared to the logics without ANN models. This is due to the reduction of unnecessary energy consumption for over-heating, -cooling, -humidifying, and -dehumidifying.
- Two proposed logics having PMV as control variables were expected to use more energy in winter while less energy in summer than did the other two logics having temperature and humidity as control variables. This is due to the higher specified comfort ranges for PMV than for air temperature and humidity, which cause two PMV-based logics to require more heating and humidifying in winter while less cooling and dehumidifying in summer.

3.4 Summary

Conventional simplistic thermal control method for residential buildings frequently creates uncomfortable thermal conditions and consumes unnecessary energy for conditioning. This is because of (1) the lack of the advanced thermal control logic, and (2) lack of the integrated control system. Although recently introduced ANN-based control methods improve thermal conditions, they take only the air temperature into account as control variable, but other significant thermal factors such as humidity and

PMV were not considered. In addition, ANN models developed for predictive control need to be tested their adaptability through performance test for diverse situations.

Upon these problems, this study aimed to develop ANN-based advanced residential thermal control methods for providing more comfortable thermal conditions in terms of air temperature, humidity or PMV, and to investigate their energy efficiency. Developed methods were designed to improve the residential thermal issues and to satisfy the new trends of the residential thermal control methods. For achieving these objectives, a thermal control logic framework was developed, which supports integrated, dynamic, flexible, predictive, and adaptive (model-free) control. At the same time, a control system hardware framework was also developed for integrated, dynamic, and flexible control. Performance test for the proposed control method was conducted for a change of building background conditions (architectural variables: change of orientation, envelope insulation, and window-wall-ratio) and for disturbances that buildings may experience during their life-span (architectural variables: internal load and ventilation, systematic variables: change of setback and setpoint, and exterior climatic variables: extreme change of exterior thermal conditions)

Two logics using ANN models were hypothesized to create more comfortable thermal conditions with reduced overshoot and undershoot than were logics without ANN models. In addition, they were expected to consume less energy due to the reduction of unnecessary system operation for over-heating, -cooling, -humidifying, and -dehumidifying. Meanwhile, two logics having PMV as a control variable would create a more comfortable PMV condition than would the other two logics having temperature and humidity as control variables. In addition, they were expected to use more energy in winter while less energy in summer than did the other two logics. This is due to the higher specified comfort ranges for PMV than for air temperature and humidity, which cause two PMV-based logics to require more heating and humidifying in winter while less cooling and dehumidifying in summer.

CHAPTER IV

RESEARCH DESIGN

4.1 Overview

This study consisted of four major steps: (1) development of a thermal control logic framework, (2) development of a system hardware framework, (3) application of developed control logic and system hardware, and (4) data analysis (Figure 4.1).

In the development phase of a thermal control logic framework, an overall framework of control logic and four control logics were developed as residential thermal control methods. The conventional thermal control logic utilized a thermostat and hygrometer for controlling indoor air temperature and humidity independently. On the other hand, three logics were proposed as advanced methods: (1) PMV (Predicted Mean Vote) control without ANN (Artificial Neural Network), (2) temperature and humidity control with ANNs, (3) PMV control with ANN. Among the proposed logic, two logics for conditioning PMV utilized more diverse climatic factors such as indoor MRT (Mean Radiant Temperature) and A/V (Air Velocity) as well as two personal factors such as clothing level and metabolic rate. And two predictive control logics with ANN models used predicted indoor air temperature, humidity, or PMV values in the algorithms.

In the development phase of a system hardware framework, several technical components were coordinated: sensors, data acquisition system, computer hardware, control logic, and climate control devices. While this system framework was designed to control the thermal conditions in a single zone in this study, it can be applied to multiple zonal controls or to IAQ (Indoor Air Quality) control after system expansion in the future.

In the application phase of developed control logic and integrated system hardware, two research methods were used: computer simulation and experiment. Computer simulation was the primary method for testing hypotheses while experimentation was the secondary method for verifying the results. The purpose of the application was to investigate the comparative performance of conventional and proposed logic for the diverse situations that residential buildings may experience during their life span. The first step of the application was to compare the simulation and experimental results in the same thermal module. The similarity of thermal conditions and energy consumption was presented in this step in order to verify the simulation results. The next step of the application was to test the performance of the logic for diverse variables by computer simulation for a typical U.S. home. Variables were architectural variables, system variables, and exterior climate variable. The last step of the application was to test for the basecase and the application of setback through experiment in the thermal module.

In the data analysis phase, three major factors were investigated: interior thermal comfort, features (ratio and magnitude) of overshoots and undershoots out of the specified comfort ranges, and energy efficiency.

DEVELOPMENT OF A THERMAL CONTROL LOGIC FRAMEWORK

- Conventional Control Logic
- Proposed Control Logics

⇩

DEVELOPMENT OF A SYSTEM HARDWARE FRAMEWORK

- Sensors
- Data Acquisition System
- Computer Hardware
- Control Logic
- Environmental Control Devices

⇩

APPLICATION OF DEVELOPED CONTROL LOGIC AND SYSTEM HARDWARE

- Comparison between Computer Simulation and Experiment
- Computer Simulation
  - Basecase
  - Architectural Variables
  - Systematic Variables
  - Disturbances
- Experiment
  - Basecase
  - Application of Setback

⇩

DATA ANALYSES

- Interior Thermal Comfort
- Ratio of Overshoots and Undershoots out of the Specified Comfort Ranges
- Magnitude of Overshoots and Undershoots out of the Specified Comfort Ranges
- Energy Efficiency

Figure 4.1 Procedure of Study

4.2 Development of a Thermal Control Logic Framework

A framework of control logic and four control logics, which were a conventional and three proposed logics, were developed using MATLAB and its Neural Network (NN) toolbox. Each logic has five steps for maintaining residential thermal conditions: physical condition, thermal comfort range, energy, decision of system operation, and performance of control devices. Details appear in the following sub chapters.

4.2.1 Conventional Control Logic

The conventional control logic represented the most commonly applied thermal control algorithm. It regarded indoor air temperature and humidity as target variables to be controlled. A thermostat and hygrometer detected current indoor temperature and humidity conditions, and based on which, the control logic decided the operation of the environmental control devices. In general, operations for controlling air temperature and humidity worked independently.

Five principal steps of the conventional logic are shown in Figure 4.2. It consists of physical condition, thermal comfort range, energy, decision of system operation, and operation of control devices.

In Step one, physical condition, the current interior environmental condition was measured and transferred to the control panel. The air temperature sensor (e.g., thermostat) and humidity sensor (e.g., hygrometer) were applied to it.

In Step two, thermal comfort range, users set operating ranges for heating, cooling, humidifying, and dehumidifying systems based on their preferred comfort ranges. In general, occupants used a thermostat to set their desired air temperature for heating and cooling systems.

In Step three, energy, users decided on a setback value and a period for reducing energy consumption. Because thermostats now have a function for this, occupants were able to set the setback air temperature and time for the heating and cooling systems.

In Step four, decision of system operation, the control algorithm decided the operation of environmental control devices. Previously acquired information, such as the current climatic condition, operating range, and setback, was utilized in this step. The conventional logic usually employed two independent algorithms for controlling air temperature and humidity, respectively.

In Step five, operation of control devices, the control devices such as HVAC systems or independent domestic thermal control devices work for improving thermal conditions based on the signals decided in the previous control logic.

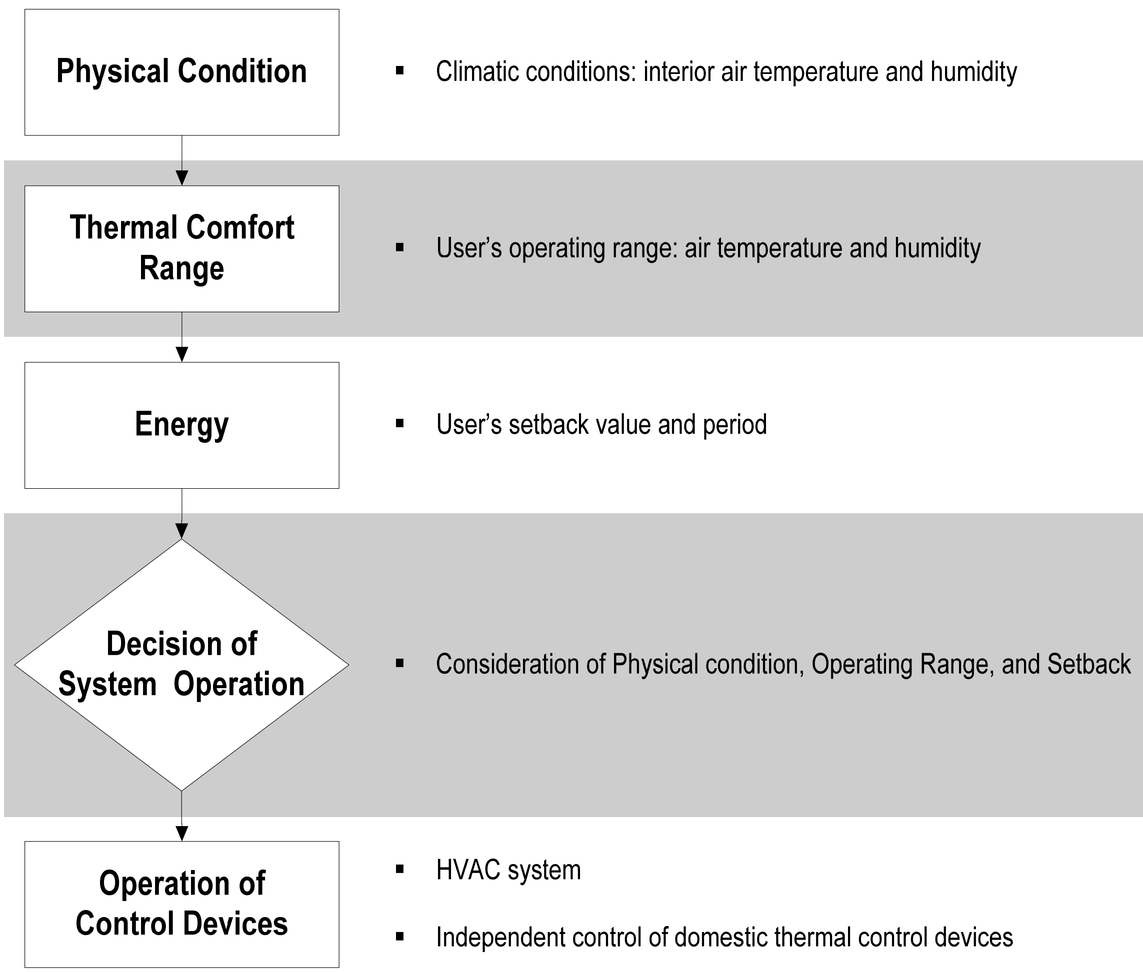

Figure 4.2 Flow of the Conventional Thermal Control Logic

Algorithm for Air Temperature Control

Detail of the algorithm for air temperature control appears in Figure 4.3.

If a heating system is working:

- Compare current air temperature and the operating range.
- If current air temperature is higher than the upper limit of the operating range for heating, then "STOP Heating."
- If current air temperature is lower than the upper limit of the operating range for heating, then "CONTINUE Heating."

If a heating system is not working, ask whether a cooling system is working.

If a cooling system is working:

- Compare current air temperature and the operating range.
- If current air temperature is lower than the low limit of the operating range for cooling, then "STOP Cooling."
- If current air temperature is higher than the low limit of the operating range for cooling, then "CONTINUE Cooling."

If a cooling system is not working (i.e., neither system is working):

- Compare current air temperature and the operating ranges.
- If current air temperature is higher than the upper limit of the operating range for cooling, then "START Cooling."
- If current air temperature is lower than the low limit of the operating range for heating, then "START Heating."
- Or (i.e., current air temperature is between the upper limit of the operating range for cooling and the low limit of the operating range for heating), "Do Nothing."

Algorithm for Humidity Control

Detail of the algorithm for humidity control appears in Figure 4.4.

If a humidifying system is working:

- Compare current humidity and the operating range.
- If current humidity is higher than the upper limit of the operating range for humidifying, then "STOP Humidifying."
- If current humidity is lower than the upper limit of the operating range for humidifying, then "CONTINUE Humidifying."

If a humidifying system is not working, ask whether a dehumidifying system is working.

If a dehumidifying system is working:

- Compare current humidity and the operating range.
- If current humidity is lower than the low limit of the operating range for dehumidifying, then "STOP Dehumidifying."
- If current humidity is higher than the low limit of the operating range for dehumidifying, then "CONTINUE Dehumidifying."

If a dehumidifying system is not working (i.e., neither system is working):

- Compare current humidity and the operating ranges.
- If current humidity is higher than the upper limit of the operating range for dehumidifying, then "START Dehumidifying."
- If current humidity is lower than the low limit of the operating range for humidifying, then "START Humidifying."
- Or (i.e., current humidity is between the upper limit of the operating range for dehumidifying and the low limit of the operating range for humidifying), "Do Nothing."

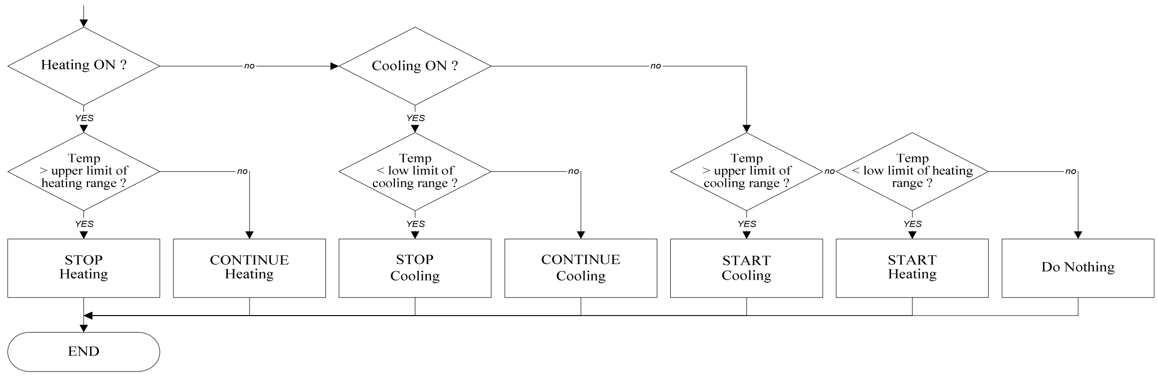

Figure 4.3 Algorithm for Air Temperature Control

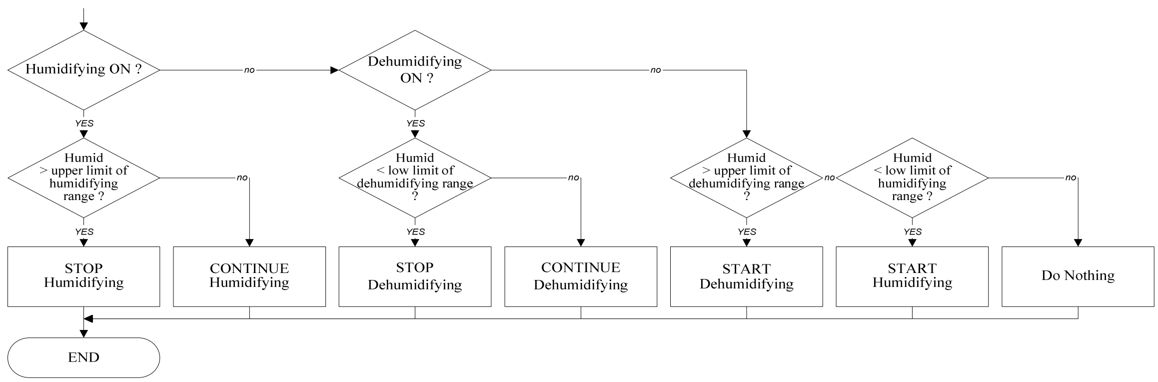

Figure 4.4 Algorithm for Humidity Control

A Complete appearance of the conventional logic can be found in Figure 4.5.

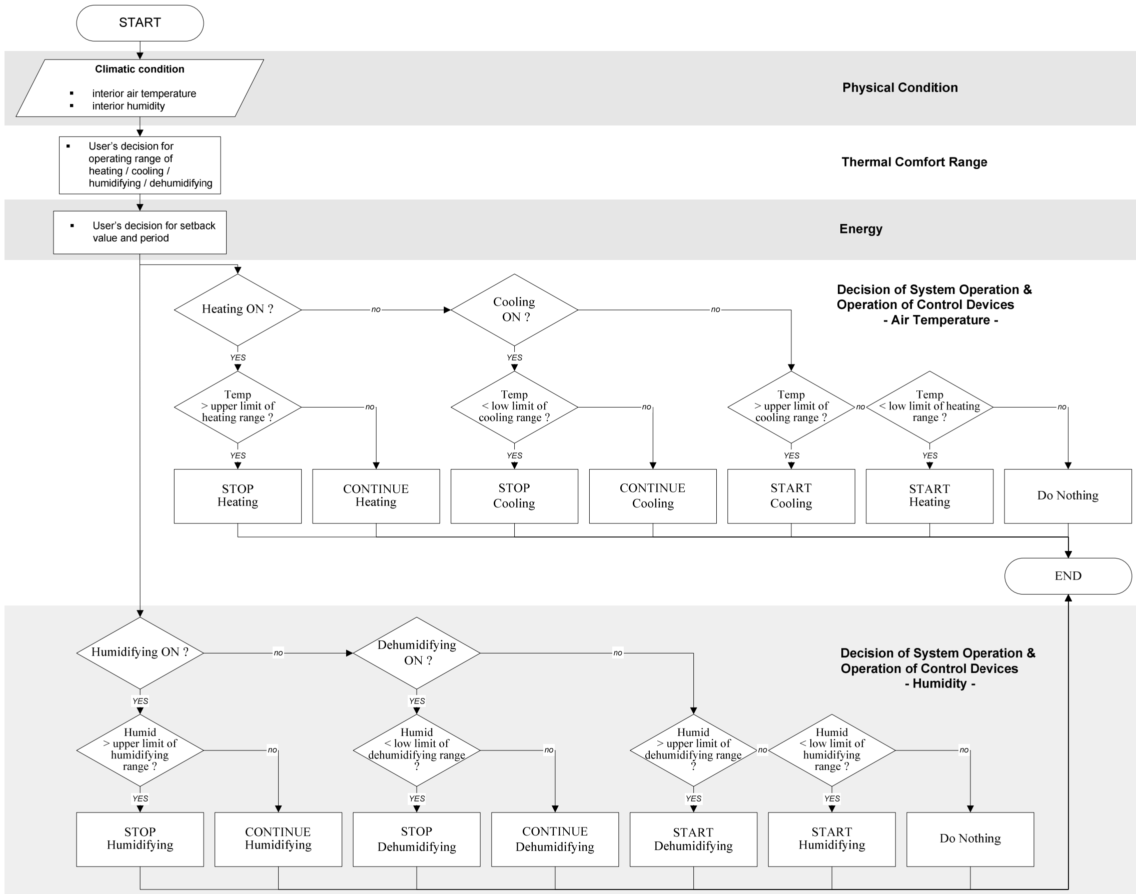

Figure 4.5 Complete Conventional Control Logic for Controlling Air Temperature and Humidity

4.2.2 Proposed Control Logic

Proposed control logic was designed to improve thermal conditions and energy efficiency. Three logics were developed for this study: (1) PMV control without ANN, (2) temperature and humidity control with ANNs, and (3) PMV control with ANN. While the proposed logic had the same steps as the conventional logic, they included advanced features (bold characters): use of more diverse climatic information of the interior and exterior as well as personal conditions; recommendation of comfort range and setback operations; application of ANN models in algorithms (Figure 4.6).

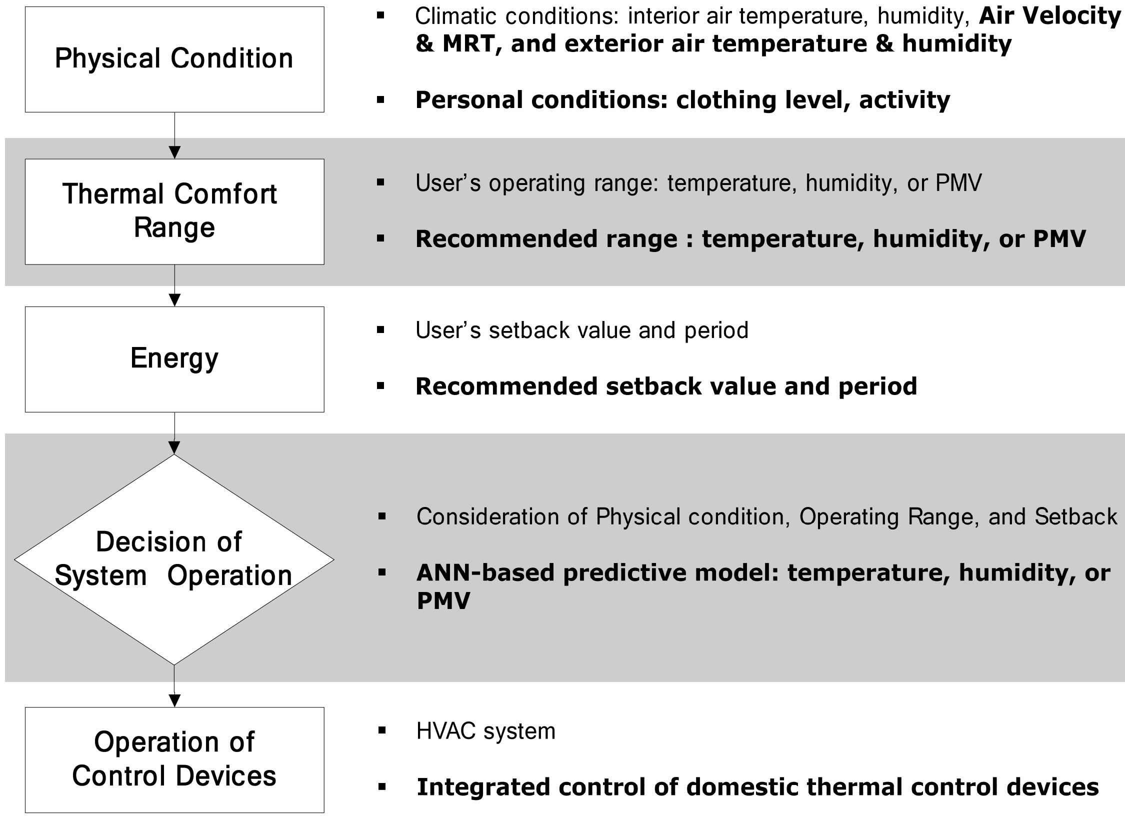

Figure 4.6 Flow of the Proposed Thermal Control Logic

4.2.2.1 Physical Condition

Two principal types of information were collected: climatic conditions and personal conditions. Current interior air temperature, humidity, air velocity, MRT (Mean Radiant Temperature), and exterior air temperature and humidity were measured and transferred to the control panel as climate conditions. Occupant clothing level and activity were also utilized for calculating PMV in the algorithms. This step of each proposed logic is illustrated in Figures 4.7, 4.8, and 4.9.

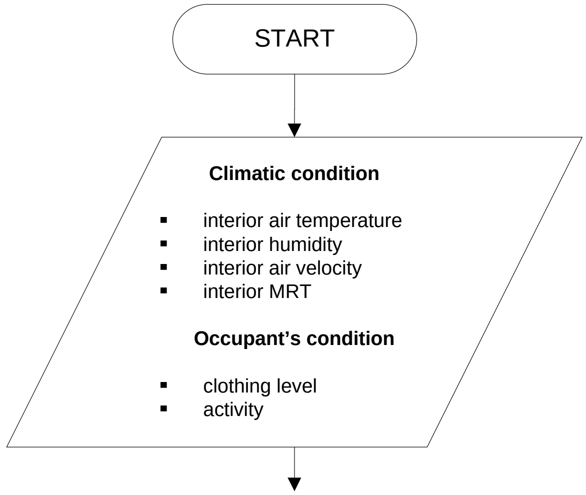

Figure 4.7 Physical Condition: PMV Control without ANN

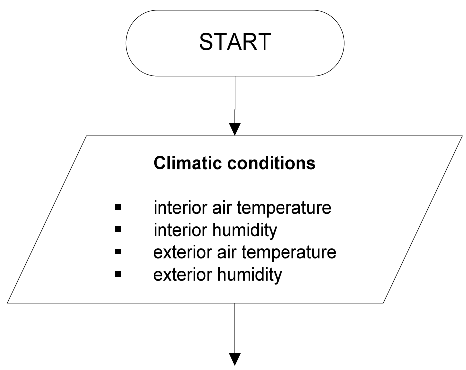

Figure 4.8 Physical Condition: Temperature and Humidity Control with ANNs

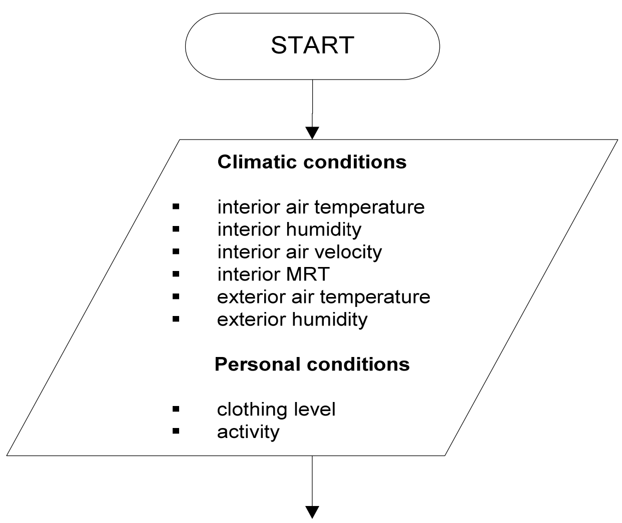

Figure 4.9 Physical Condition: PMV Control with ANN

4.2.2.2 Thermal Comfort Range

Besides the user's decision as to thermal comfort ranges, proposed logic recommended the optimal comfort ranges for systems operation. Once the recommended ranges were selected for use, the algorithm sets the comfort range for air temperature, humidity, or PMV as follows based on the ASHRAE Standard [ASHRAE (1992), ASHRAE (1989)]. This step of each proposed logic is illustrated in Figures 4.10 and 4.11.

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

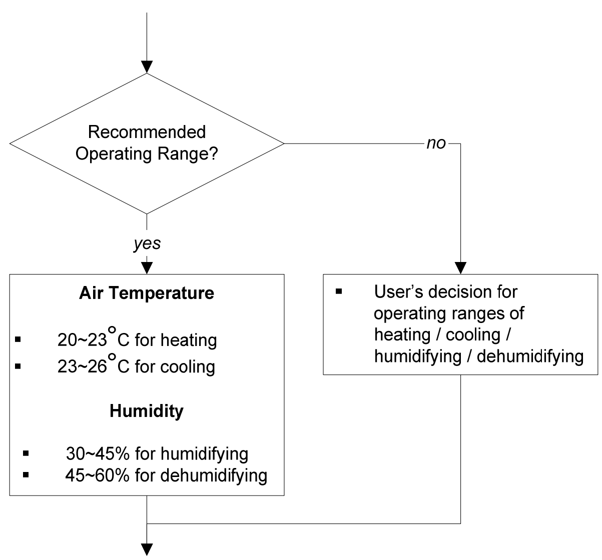

Figure 4.10 Thermal Comfort Range: Temperature and Humidity Control with ANNs

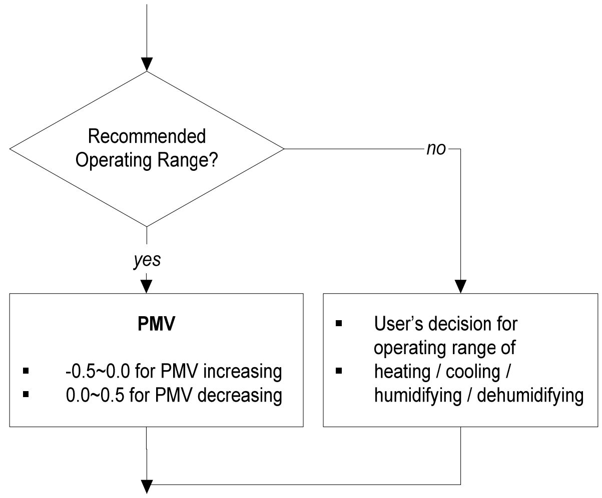

Figure 4.11 Thermal Comfort Range: PMV Control without ANN and PMV Control with ANN

4.2.2.3 Energy

Besides the user's decision as to setback mode for environmental control devices, proposed logic recommended setback values and periods for saving energy. Once the recommended values and period were selected for use, the control algorithm sets the setback modes for air temperature, humidity, or PMV. Embedded setback values and periods for air temperature, humidity and PMV are illustrated in Figures 4.12, 4.13, and 4.14. In order to prevent energy waste, a zero-band strategy was applied. For example, the operating ranges of the heating device and cooling device were not allowed to overlap. This step of each proposed logic is illustrated in Figures 4.15 and 4.16.

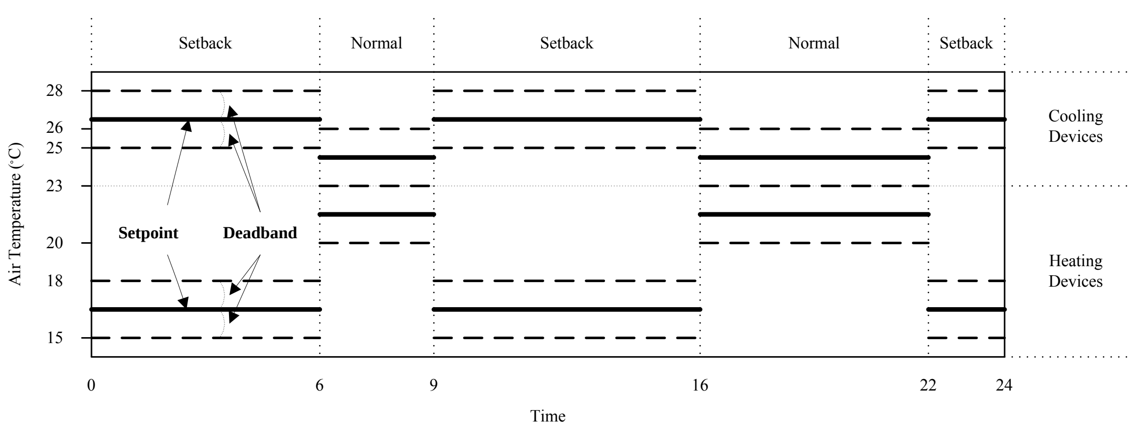

Figure 4.12 Operating Mode for Air Temperature Control Devices

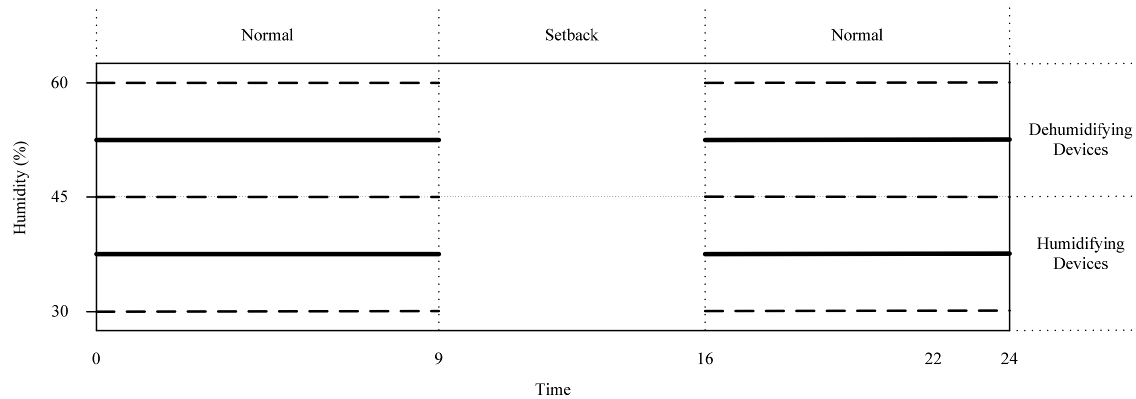

Figure 4.13 Operating Mode for Humidity Control Devices

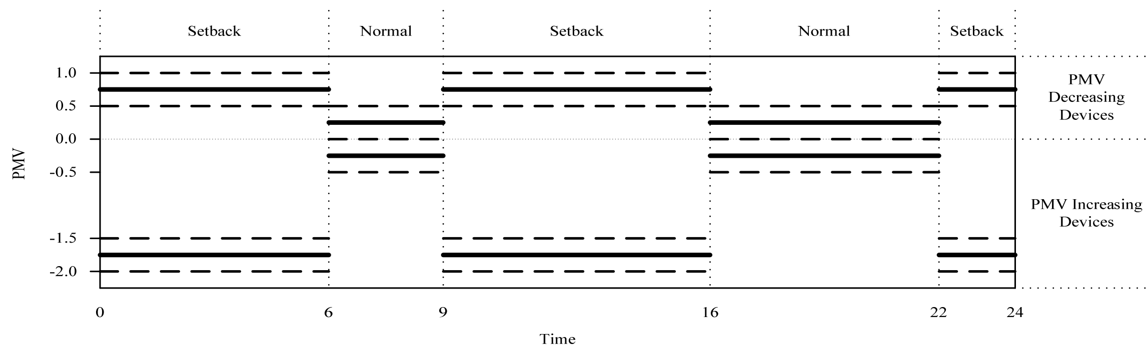

Figure 4.14 Operating Mode for PMV Control Devices

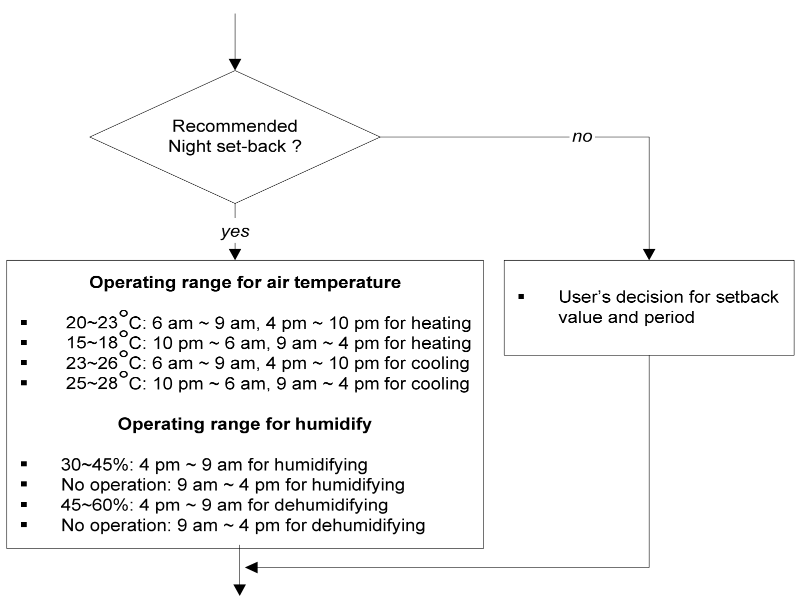

Figure 4.15 Energy: Temperature and Humidity Control with ANNs

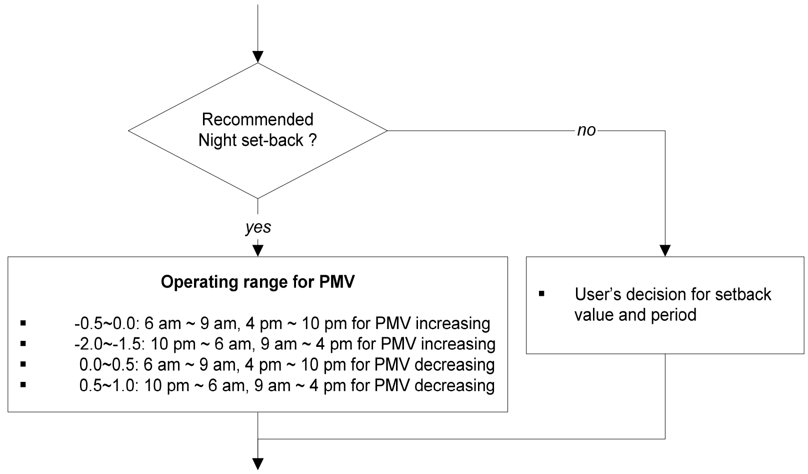

Figure 4.16 Energy: PMV Control without ANN and PMV Control with ANN

4.2.2.4 Decision of System Operation and Operation of Control Devices

Algorithms decided the operations of the control devices based on the physical condition, operating range, and set-back value and period. In particular, ANN models were applied in ANN-based logic to predict future thermal conditions. Figure 4.17 conceptually describes how an ANN model works in the algorithm for a more comfortable air temperature condition. It compares the air temperature variations by the conventional logic and the proposed logic utilizing an ANN model. 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, ΔTemperature is the maximum rise of temperature after stopping the currently working heating device. ANN models for predicting humidity and PMV work the same way for conditioning humidity and PMV, respectively.

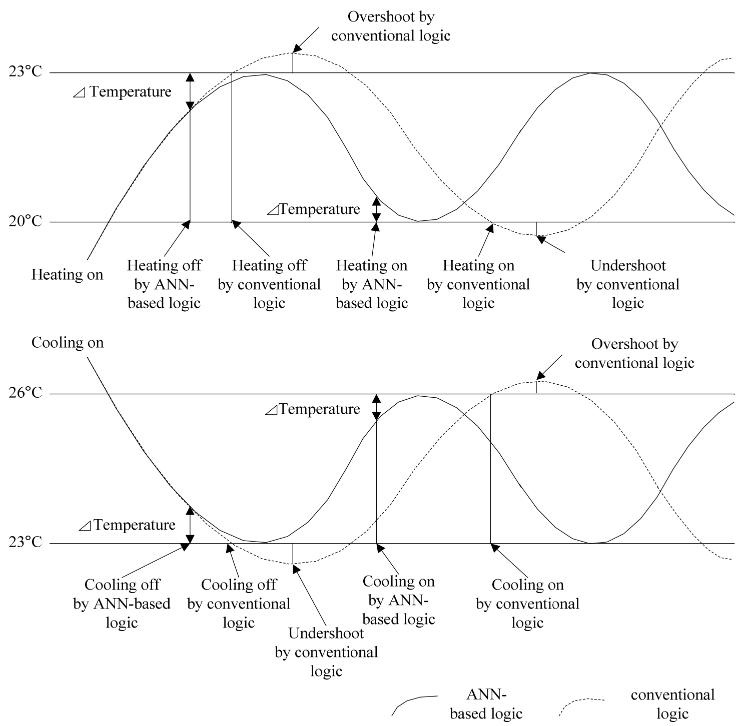

Figure 4.17 Comparison of Air Temperature Variation between Conventional Logic and Predicted Control with ANN Model

The structure of ANN models for predicting air temperature, humidity, and PMV is given in Figure 4.18. 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 the decision of the number of hidden layer, number of hidden neurons, number of training data sets, training goals, epoch, learning rate, and momentum. 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 4.1 [Yang, I. H., et al. (2003), Datta, D, 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 4.2

[Kalogirou, S. A., et al., (2000)]. 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.

$N_h = 2*N_i + 1$ .... (Equation 4.1)

$N_d = (N_h - 1/2*(N_i + N_o))^2$ .... (Equation 4.2)

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, I. H., 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), Yang, I. H., et al (2003)].

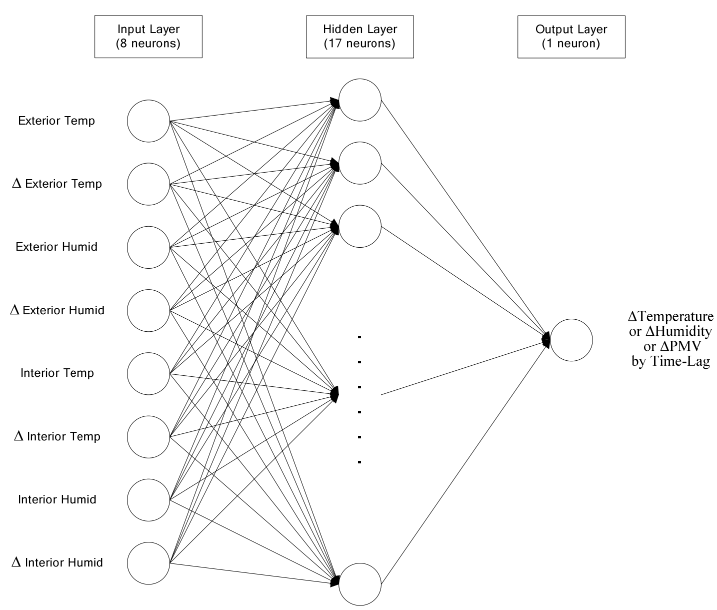

Figure 4.18 Structure of ANN Models

Algorithms for decisions about device operation are given in Figures 4.19 to 4.22. While a current PMV value was a determinant of operation in Figure 4.19, a current PMV and a predicted ΔPMV by the ANN model were factors deciding operation in Figure 4.22. In the meantime, predicted ΔTemperature and ΔHumidity by ANN models were utilized for conditioning air temperature and humidity in Figures 4.20 and 4.21 respectively.

<u>Algorithm for PMV Control without ANN</u>

Details of the algorithm of PMV control without ANN appear in Figure 4.18.

If PMV increasing systems are working:

- Compare current PMV and the operating range.
- If current PMV is higher than the upper limit of the operating range for PMV increasing, then "STOP PMV Increasing (e.g., heating and humidifying)."
- If current PMV is lower than the upper limit of the operating range for PMV Increasing, then "CONTINUE PMV Increasing."

If PMV increasing systems are not working, ask whether PMV decreasing systems are working.

If PMV decreasing systems are working:

- Compare current PMV and the operating range.
- If current PMV is lower than the low limit of operating range for PMV decreasing, then "STOP PMV Decreasing (e.g., cooling and dehumidifying)."
- If current PMV is higher than the low limit of operating range for PMV decreasing, then "CONTINUE PMV Decreasing."

If PMV decreasing systems are not working:

- Compare current PMV and the operating ranges.
- If current PMV is higher than the upper limit of operating range for PMV decreasing, then "START PMV Decreasing."

- If current PMV is lower than the low limit of operating range for PMV Increasing, then “START PMV Increasing.”
- Or (i.e., current PMV is between the upper limit of the operating range for PMV decreasing and the low limit of the operating range for PMV increasing), “Do Nothing.”

Algorithm for Air Temperature Control with ANN

The algorithm for air temperature control with ANN is identical to the algorithm for conventional air temperature control logic except that a predicted ΔTemperature by ANN model was used as a determinant along with the current air temperature (Figure 4.20).

Algorithm for Humidity Control with ANN

The algorithm for humidity control with ANN is also identical to the algorithm for conventional humidity control logic except that a predicted ΔHumidity by the ANN model was used as a determinant along with current humidity (Figure 4.21).

Algorithm for PMV with ANN

The algorithm for PMV control with ANN is also identical to the algorithm for PMV control without ANN except that a predicted ΔPMV by the ANN model was used as a determinant along with current PMV (Figure 4.22).

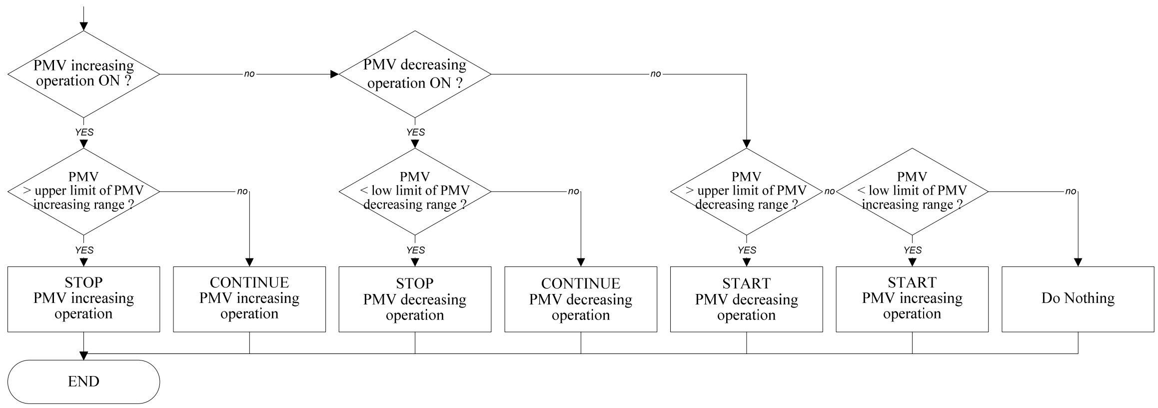

Figure 4.19 Algorithm of PMV Control without ANN

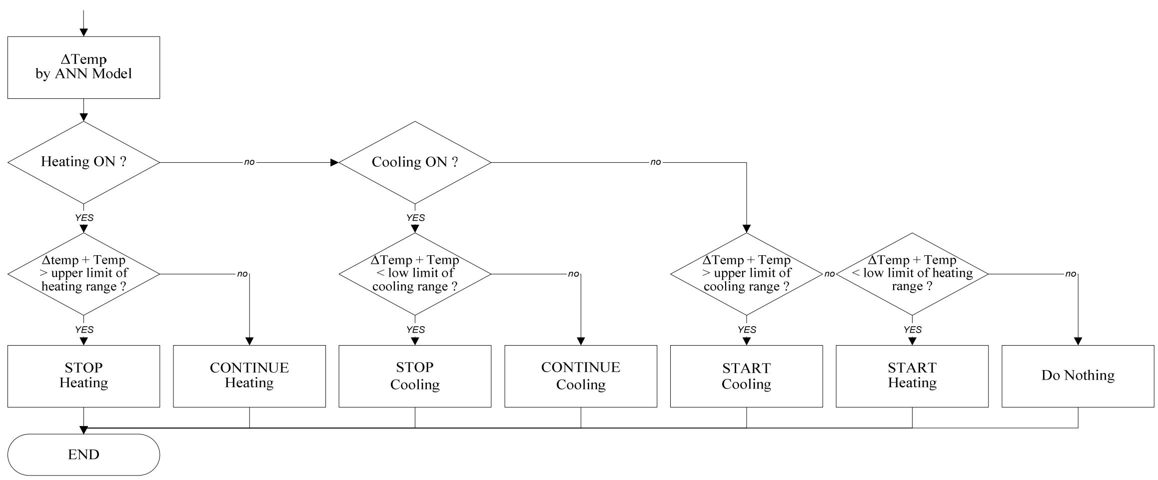

Figure 4.20 Algorithm of Temperature Control with ANN

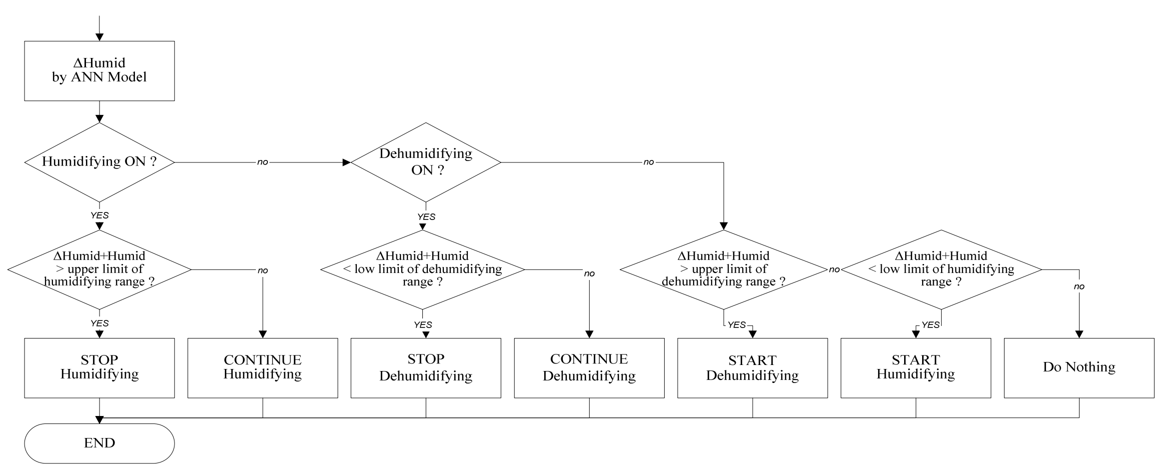

Figure 4.21 Algorithm of Humidity Control with ANN

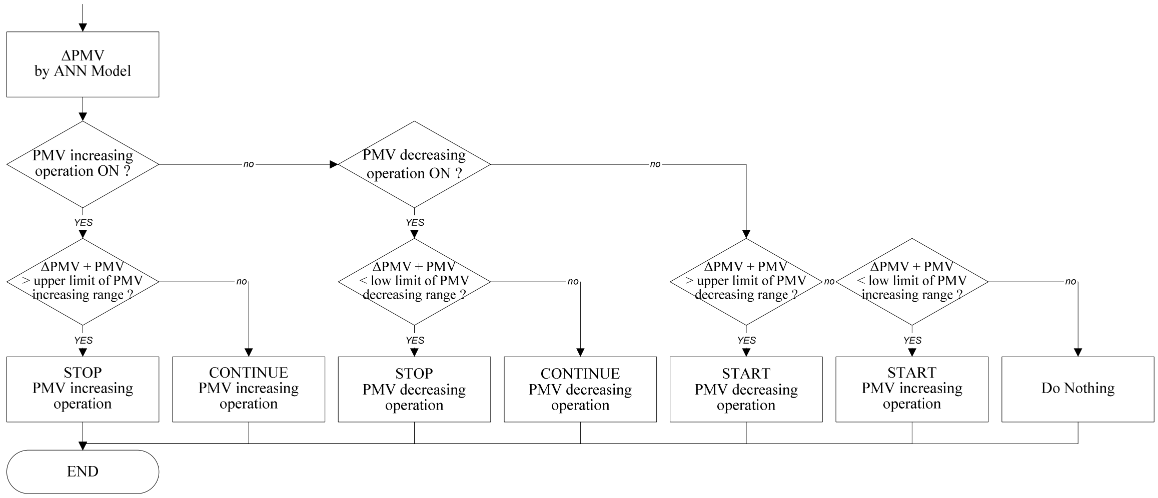

Figure 4.22 Algorithm of PMV Control with ANN

4.2.2.5 Overall Procedure of Proposed Thermal Control Logics

Three proposed control logics are illustrated in Figures 4.23, 4.24, and 4.25. Each logic combined five major steps: physical condition, thermal comfort range, energy, decision of system operation, and operation of control devices. In particular, the control logic of temperature and humidity control with ANNs controls air temperature and humidity independently based on its own decision process.

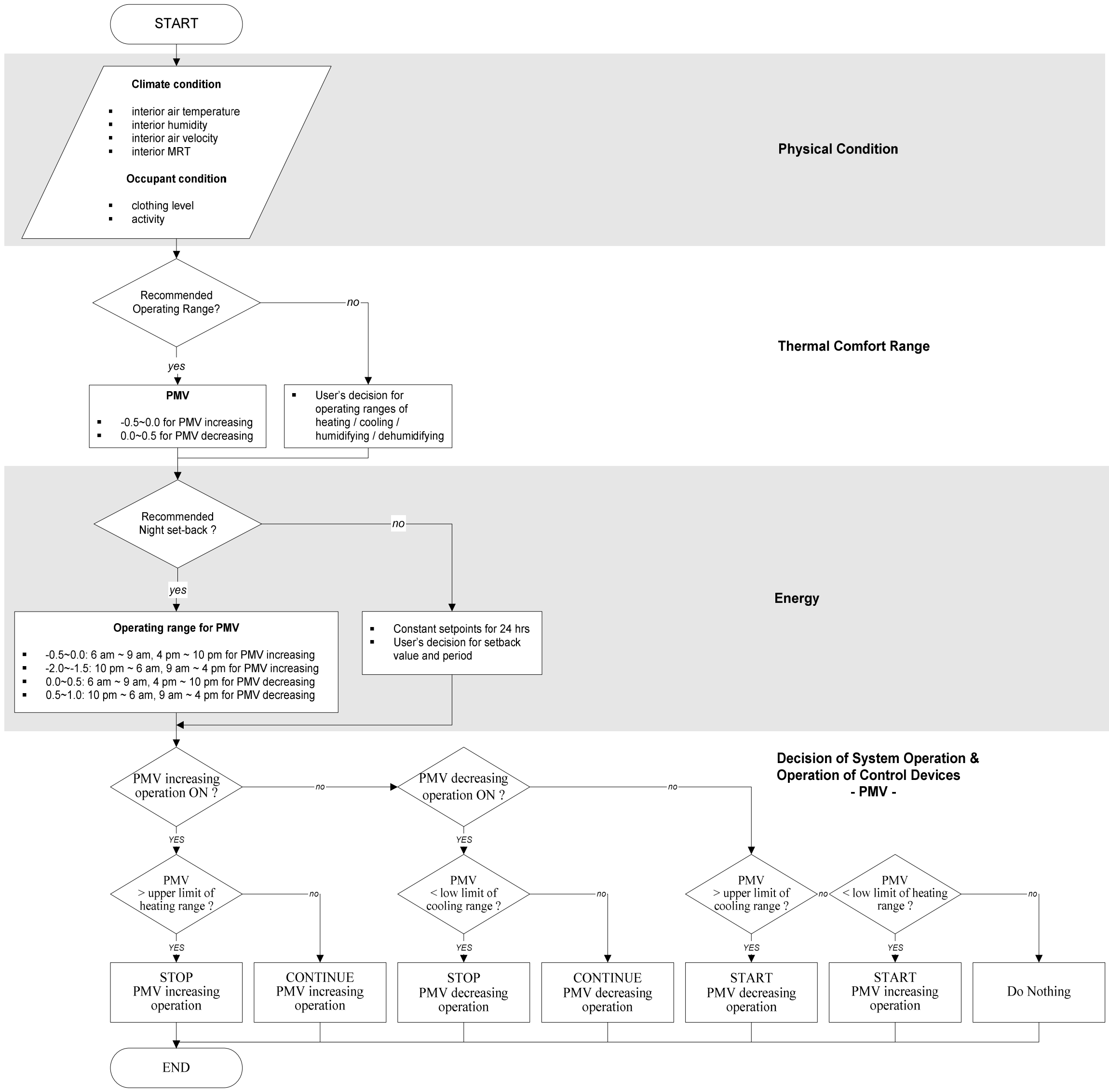

Figure 4.23 Complete Logic of PMV Control without ANN

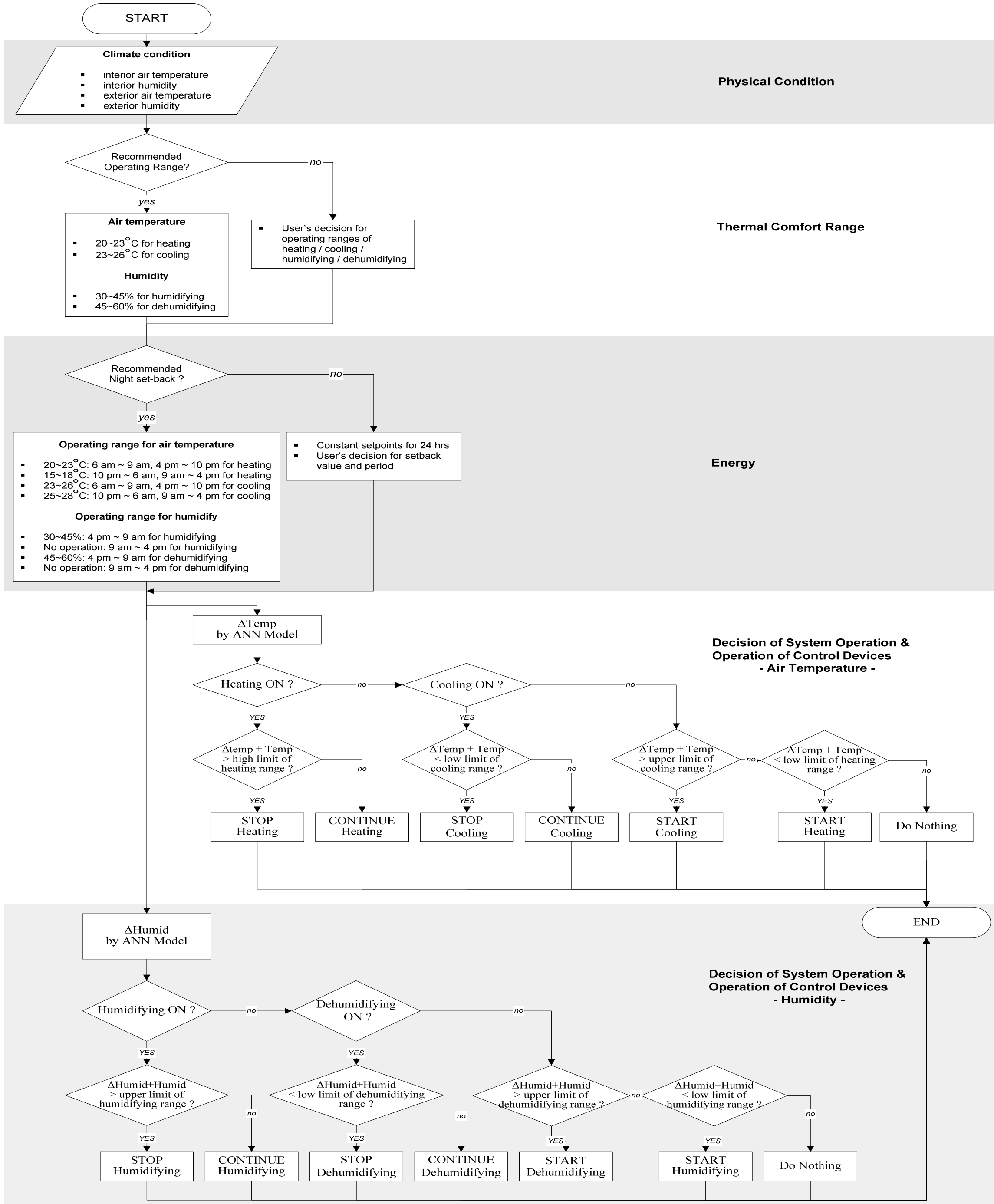

Figure 4.24 Complete Logic of Temperature and Humidity Control with ANNs

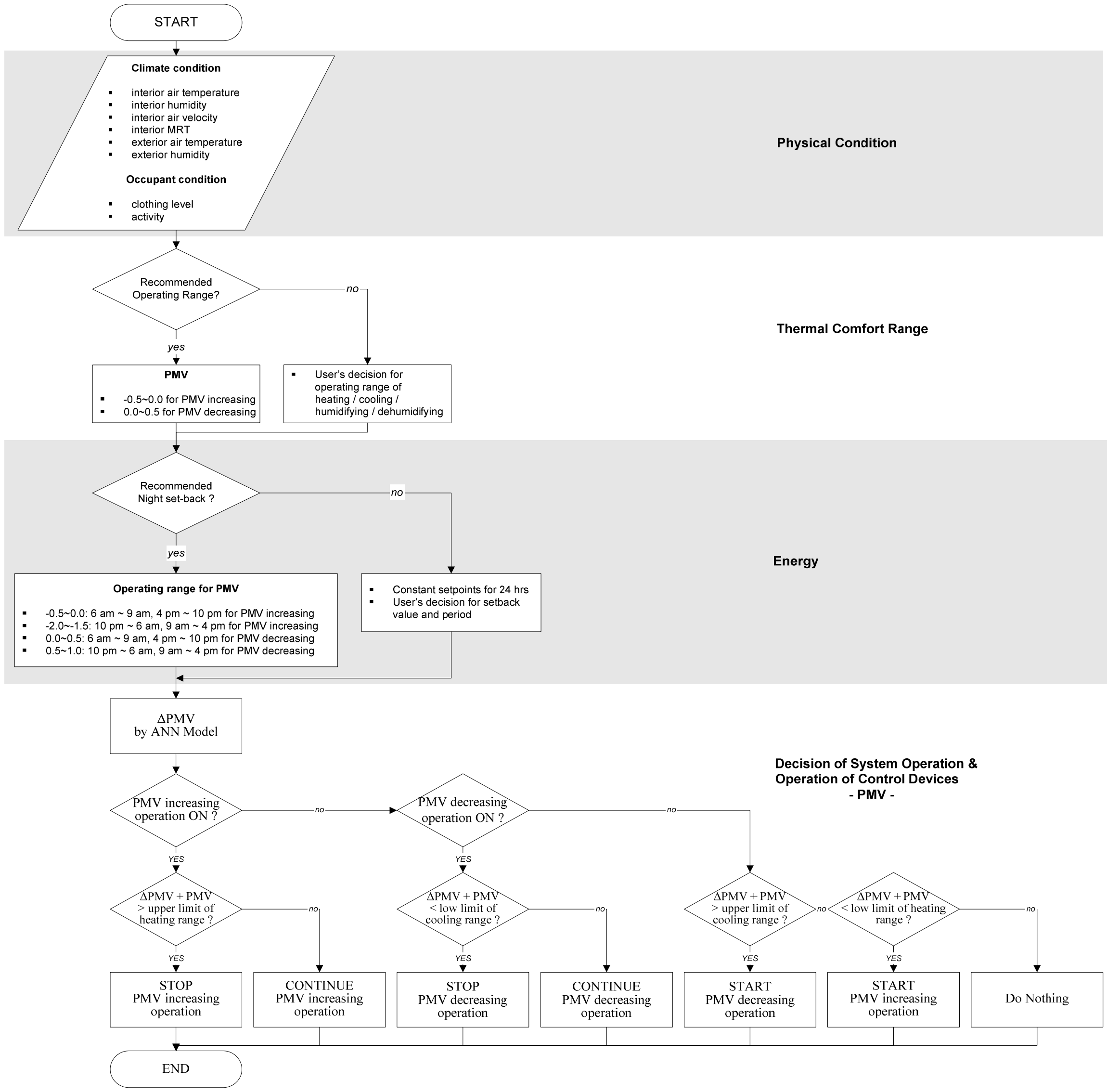

Figure 4.25 Complete Logic of PMV Control with ANN

4.3 Development of a System Hardware Framework

A control system hardware framework was developed for the optimal thermal control through the integrated information on climate conditions and the coordinated device operation. The structure of the integrated system appears in Figure 4.26. First, the interior and exterior thermal quality parameters were monitored: air temperature and humidity from the exterior; air temperature, humidity, MRT, and air velocity from the interior. Monitoring was done by sensors located in exterior and interior spaces. Monitored data from analog-type was transferred to the data acquisition system. An

EZIO card was utilized as a data acquisition board, and its six analog slots were allocated to each sensor for data conversion from analog to digital. Digitalized signals were used as inputs in the control logic. Output signals for the control devices were decided by the control logic developed with the data acquisition toolbox and ANNs toolbox in MATLAB, which are inventories of frequently used programming functions. One analog type output slot for linear output and three digitalized output slots for on/off on the EZIO card were then assigned for data conversion from digital to analog. A heater, A/C, humidifier, and dehumidifier were installed as environmental control devices with signal amplifiers using relays.

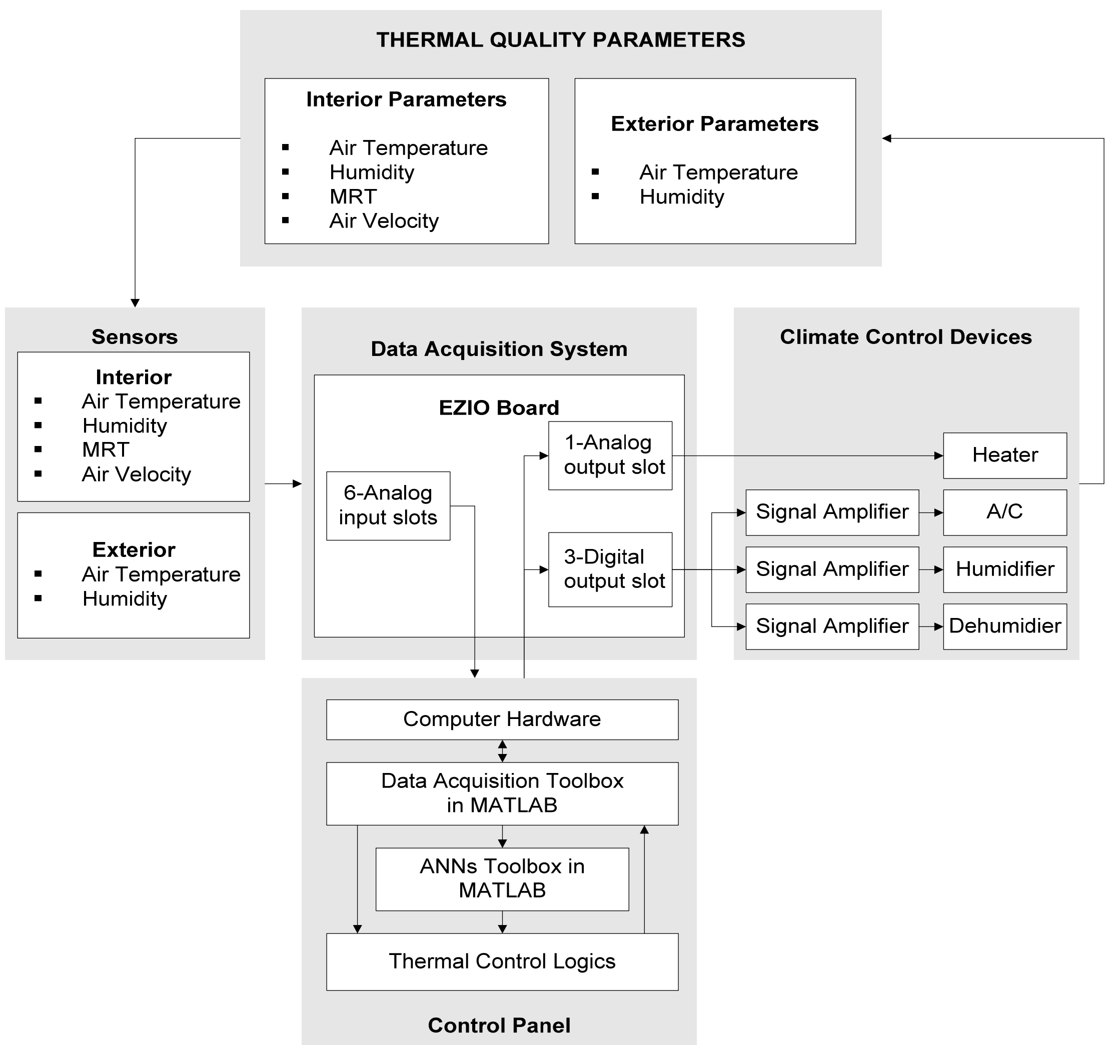

Figure 4.26 Structure of Framework of Integrated Control System Hardware

4.3.1 Sensors

In order to transmit the interior and exterior thermal conditions to the data acquisition system, four sensor products were installed in the framework. Their specifications appear in Table 4.1.

Appearances	Names	Targets Monitored	Measure Ranges	Output Ranges	Accuracy	Manufacturers
	EE70 Temp/AV Transmitter	Interior Temperature and A/V	0 ~ 50 °C	4 ~ 20 mA	±0.5°C at 20°C; ±0.05 m/s + 0.5% of measuring value	Global Controls Inc (2005)
	HU-1142 RH Transmitter	Interior Humidity	10 ~ 90%	4 ~ 20 mA	±2% RH	DWYER (2004)
	LM35CAG Transmitter	Interior MRT	0 ~ 110 °C	4 ~ 20 mA	±0.2°C at 25°C	National Semi-conductor (2008)
	HX93A Temp/RH Transmitter	Exterior Temperature and Humidity	-20 ~ 75 °C 3 ~ 95%	4 ~ 20 mA	±0.6°C at 25°C; ±2.5% RH from 20 to 80% RH	OMEGA (2007)

Table 4.1 Description of Sensor Products

4.3.2 Data Acquisition System

Three boards were applied as the data acquisition system: one board to convert from current to voltage, an EZIO data acquisition board, and one board for signal magnification.

The first board consists of pairs of two types of resistances were assigned to each sensor input (Figure 4.27). Total resistance of each pair was 250Ω (240Ω and 10Ω). These resistances converted electrical signal from 0~20 mA current to 0~5 V of voltage.

The next board was an EZIO board had 8-analog input slots, 2_PWM output slot (linear type signal – analog type), and 10-digital input and output slots (on/off type signal, digital type). Among these, six analog input slots, one PWM output slot, and 3 digital output slots were used. While the board was able to communicate signals with a computer serial port, communication was also possible with a USB (Universal Serial Bus) port through a transformation adaptor [NIQ (2006)] (Figure 4.28).

The last board consists of pairs of two types of relays for signal magnification. The magnified signal was used for operating control devices such as A/C, humidifier, and dehumidifier. They worked in tandem for magnifying power in two steps. The first relay (OEG RU 250) connected its circuit when a 5.0 V and 20 mA signal came from a digital output slot on the EZIO board, which meant the turning on signal from a control algorithm. This operation allowed electrical flow of 5.0 V and 0.5 A in its circuit, by which the second relay (OEG SRUDH-SS-1092) connected its circuit. The connection of the second circuit allowed electrical flow up to 1,500 Watt with a 110 V power supply. Through this process, control signals from the EZIO board were able to operate the environmental control devices such as the A/C, humidifier, and dehumidifier (Figure 4.29).

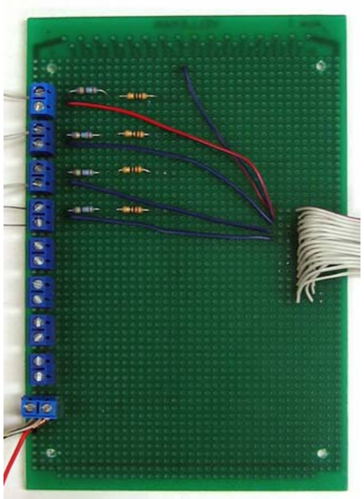

Figure 4.27 I to V Conversion

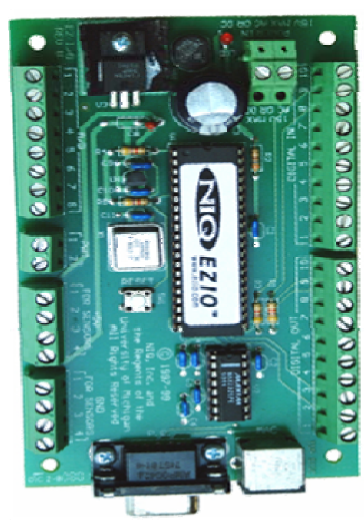

Figure 4.28 EZIO Board

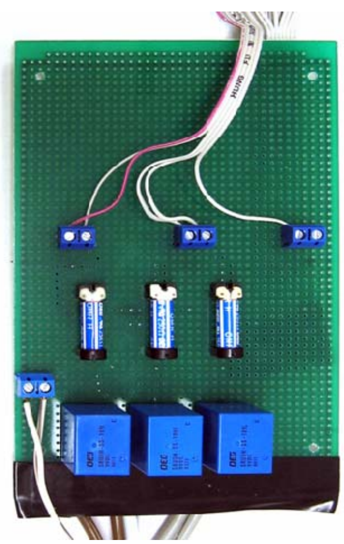

Figure 4.29 Signal Magnification

4.3.3 Computer Hardware

One desktop personal computer was used as computer hardware for data management and logic modeling. Specifications are summarized in Table 4.2.

Computer Type	Product Name	CPU	RAM	Hard Drive
Desktop PC	e-machines T3522	Celeron(R) CPU 3.33GHz	512 MB	100 GB

Table 4.2 Description of Computer Specification

4.3.4 Control Logic

A conventional logic and three proposed logics were developed with MATLAB software. Two toolboxes “Data Acquisition Toolbox” and “Neural Network Toolbox” in the MATLAB were applied to data acquisition and ANN modeling, respectively [MathWorks (2005)].

4.3.5 Environmental Control Devices

Four types of environmental control devices were installed in the integrated framework. While they were home appliances originally designed to work independently, they followed the output signals from the control logic and were designed to work together in this study (Table 4.3).

Appearances	Names	Types	Capacity	Manufacturers
	2069 ET	Radiant Heater	1,500 watts of Heat Supply	Lakewood Engineering
	VZ354144 (s/n)	A/C	5,050 BTU of Heat Remove	General Electric
	VS100 Cool and Warm Ultrasonic Humidifier	Humidifier	470 ml/hr of Moisture Supply	VENTA SONIC
	30 pint dehumidifier	Dehumidifier	690 ml/hr of Moisture Remove	LG

Figure 4.3 Description of Environmental Control Devices

4.4 Application of Control Logic and Integrated System Hardware

Performance tests have been conducted for three steps: (1) comparison between computer simulation and experiment, (2) computer simulation, and (3) experiment. Through the computer simulation and experiment, the performance of the conventional and the proposed control logic was tested for the diverse situations which residential buildings may experience.

4.4.1 Comparison between Computer Simulation and Experiment

This study applied computer simulation and experiment to test hypotheses. Before the main tests for diverse variables were conducted, results of simulation and an experiment for a simple case were compared as triangulation. Similarity of the interior thermal conditions and energy consumption in this step would strengthen the validity of the simulation and experimental results of the main test.

4.4.1.1 Test Chamber

A thermal chamber was built for the experiment. A layout of the setting is visually illustrated in Figure 4.30. It had dimensions of 2.92m (width) * 2.39m (depth) * 2.51m (height) and faced outside with one window and wall, while the other three envelopes were surrounded by interior spaces. The south-facing window was covered with several styrofoam panels to block solar radiation to the interior. The east side interior wall had a window for installation of an air conditioner. Sizes and R-values of each envelope including surface air films are given in Table 4.4. Sensors for measuring and transferring thermal information were installed in the interior and exterior: air temperature and humidity sensor in the exterior; air temperature, humidity, A/V, and MRT sensors in the center of the interior at a 1.2 m height. A HOBO-U12 temperature and humidity data logger for measuring the thermal condition of surrounding interior space was located in the north-west side of the chamber [MicroDAQ (2008)]. A control panel composed of a desktop PC and control logic, was located in the outside of the chamber. A radiant heater, A/C, humidifier, and dehumidifier were installed as environmental control devices. Figures 4.31 to 4.34 show appearances of the thermal chamber and sensor compositions.

The same chamber was modeled for the computer simulation by IBPT (International Building Physics Toolbox), which is a toolbox for calculating building dynamics in conjunction with MATLAB and Simulink (Figure 4.35) [IBPT (2008)]. It had identical sizes and R-values for the envelopes. It assumed that the ventilation rate of the chamber was 1.0 ACH, which is a moderate rate for buildings.

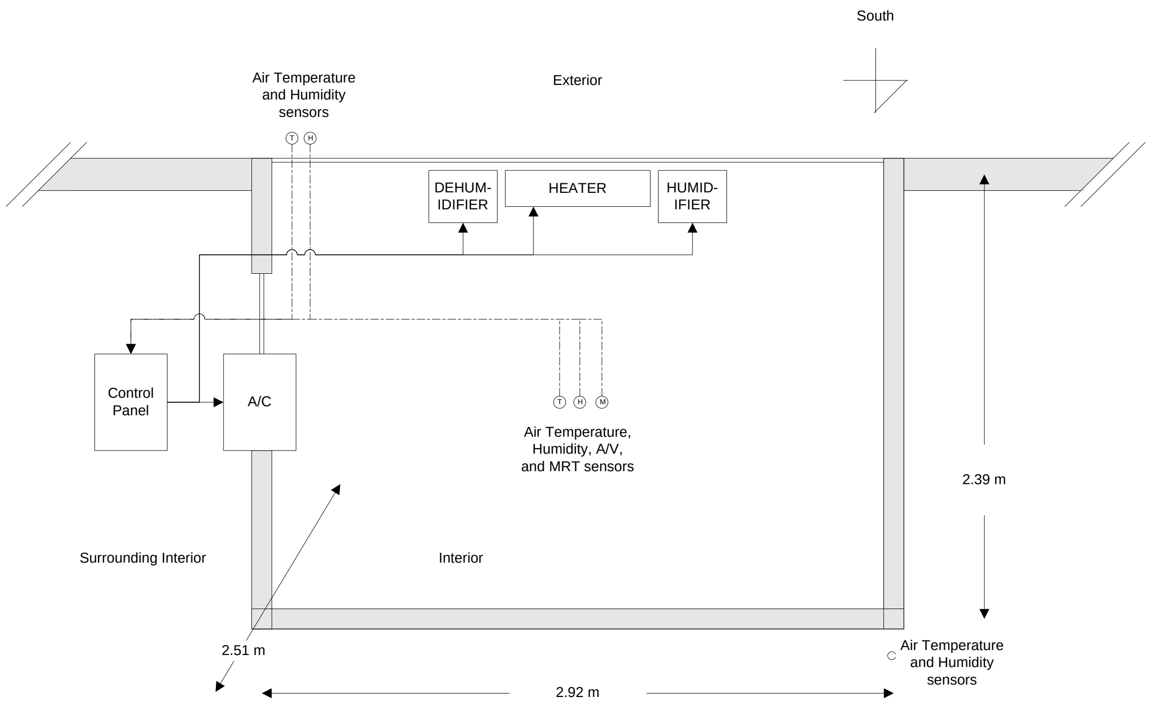

Figure 4.30 Thermal Chamber Built for Experiment

Figure 4.31 Front View of Chamber

Figure 4.32 View from Interior: East Side

Figure 4.33 Exterior Weather Station

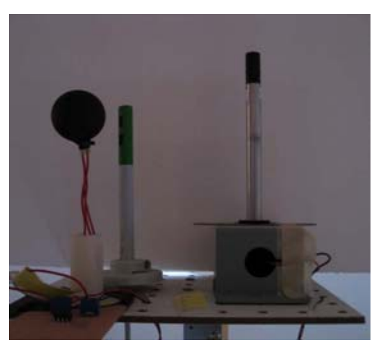

Figure 4.34 Interior Weather Station

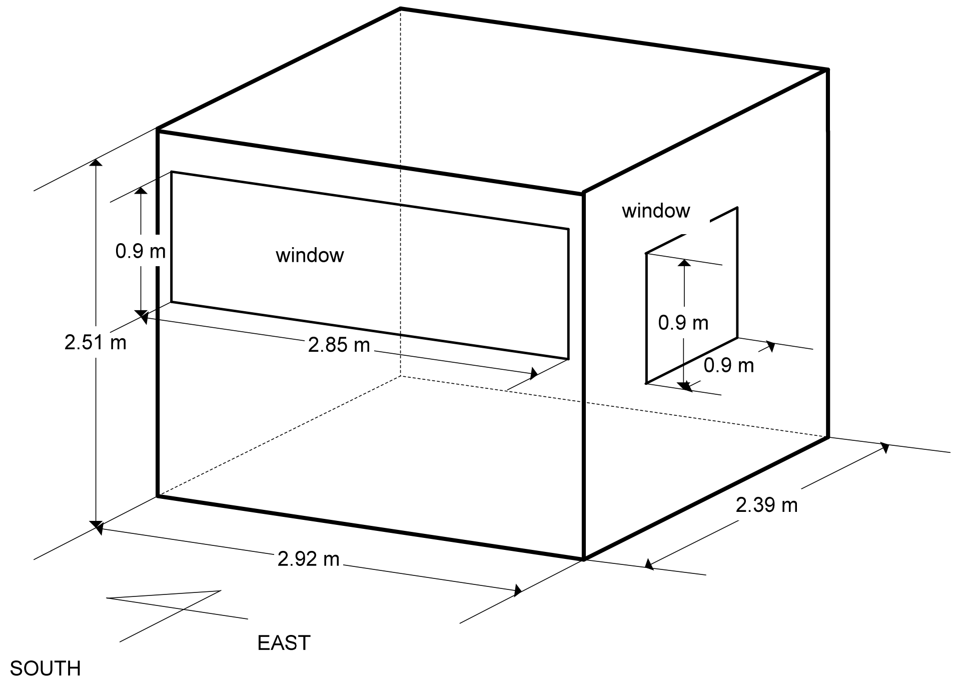

Figure 4.35 Modeling of Thermal Chamber for Computer Simulation

Envelopes		R-values (m^2*°C/W for SI, ft^2*°F/Btuh for U.S.)	Size (m*m)	Note
Walls	South	1.8 (10.3 U.S.)	2.92*2.51	Size includes window area
	East	3.6 (20.5 U.S.)	2.39*2.51	Size includes window area
	North	3.6 (20.5 U.S.)	2.92*2.51	
	West	0.18 (1.0 U.S.)	2.39*2.51	
Roof		3.6 (20.4 U.S.)	2.92*2.39	
Floor		3.7 (21.0 U.S)	2.92*2.39	
Windows	South	0.4 (2.4 U.S)	2.85*0.90	
	East	0.4 (2.4 U.S)	0.90*0.90	

Table 4.4 Specification of Envelopes

4.4.1.2 Modification of Weather Data for Computer Simulation

For the comparison of results by computer simulation and experiment, identical weather conditions would have to apply for each method. However, two principal issues first needed to be addressed.

While the air temperature data in the experiment was measured in the exterior and surrounding interior space every minute, the air temperature in the computer simulation had to be averaged hourly. Therefore, the measured air temperature in the experiment was averaged hourly for the simulation.

Then, while the actual module in the experiment faced the exterior on one envelope with the other three envelopes surrounded by interior space, the simulation model was completely surrounded by the exterior. This variation caused a different amount of heat loss and gain through the envelopes in the experiment and the simulation. Therefore, the air temperature data for the computer simulation had to be modified in order to achieve the same heat gain and loss effect in the experiment. This was accomplished using the following equation that specified the U-values and areas of each envelope (Equation 4.3). This equation generated modified air temperature data for the simulation, which was a balanced value of the exterior and surrounding spaces in the experiment.

$$T_{bal} = (T_{ex}*U_{wl\text{-}ex}*A_{wl\text{-}ex}+T_{in}*U_{wl\text{-}E}*A_{wl\text{-}E}+T_{in}*U_{wl\text{-}N}*A_{wl\text{-}N}+T_{in}*U_{wl\text{-}W}*A_{wl\text{-}W}+T_{in}*U_{rf}*A_{rf}) / (U_{wl\text{-}ex}*A_{wl\text{-}ex} + U_{wl\text{-}E}*A_{wl\text{-}E} + U_{wl\text{-}N}*A_{wl\text{-}N} + U_{wl\text{-}W}*A_{wl\text{-}W} + U_{rf}*A_{rf}) \text{.... (Equation 4.3)}$$

Where,

T_{bal}: balanced temperature

T_{ex}: exterior air temperature

T_{in}: interior air temperature

$U_{wl\text{-}ex}$: U-value of exterior wall (including window area)

$U_{wl\text{-}E}$: U-value of east wall (including window area)

$U_{wl\text{-}N}$: U-value of north wall

$U_{wl\text{-}W}$: U-value of west wall

U_{rf}: U-value of roof

$A_{wl\text{-}ex}$: area of exterior wall (including window area)

$A_{wl\text{-}E}$: area of east wall (including window area)

$A_{wl\text{-}N}$: area of north wall

$A_{wl\text{-}W}$: area of west wall

A_{rf}: area of roof

4.4.1.3 Variable

The conventional logic, which is a temperature and humidity control without ANN, was applied in the computer simulation and experiment. The period of the experiment was 0:00 to 24:00 on Dec. 23, 2007, and its exterior and surrounding air temperature data was modified for computer simulation.

4.4.1.4 Limitations

Several limitations arose when the results of the computer simulation and experiment were compared. First, the thermal mass effect in the experiment could not be counted in the computer simulation because the simulation tool did not take the thermal mass effect of the building envelope into account.

Another limitation was difference in measuring method of interior air temperature between computer simulation and experiment. Air temperature in the experiment was measured with a sensor in the middle of the chamber at a 1.2m height. The simulation tool, however, assumed that air temperature in a space was homogenous. Therefore, the results of air temperature and energy consumption could differ slightly in the experiment and simulation.

The last limitation was the possible effect of solar radiation in the experiment. In the simulation, it was assumed that there would be no solar radiation during the simulation period. On the other hand, there might be some direct and diffused solar radiation to the module in the experiment. In order to reduce this difference, the front window of the experimental module was covered with several styrofoam boards to prevent solar radiation from reaching the interior of the module.

4.4.2 Computer 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 variables 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) modeling 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)].

4.4.2.1 Control Logic

Four control logics were simulated for variables: a conventional logic and three proposed logics.

a. A conventional logic: Temperature and humidity control without ANNs

b. Three proposed logics

- PMV control without ANN
- Temperature and humidity control with ANNs
- PMV control with ANN

4.2.2.2 Target Building

A typical U.S. home was modeled in IBPT as a target building based on the U.S. Housing Survey [U.S. Census Bureau (2008)]. It was a two-story detached residential house with 184.4 m^2 ($\approx$2,000 ft^2) area. Envelopes were composed of R3.346 (R19 U.S.) wall, R6.692 (R38 U.S.) roof, R3.698 (R21 U.S.) floor, R0.606 (R3.44 U.S.) windows, and R0.215 (R1.22) doors. The WWR (window wall ratio) was 0.15 on average (0.24 for south, 0.08 for north, 0.14 for east, 0.13 for west) (Figure 4.36).

Hourly-weighted heat and moisture gains for a family of four people were considered as internal load [ASHRAE (2004), Hugh McArthur and Duncan Spalding (2004)]. A ventilation rate of 0.3 ACH (Air Changes per Hour) 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. Details of inputs are in Appendix A. Input of the Computer Simulation.

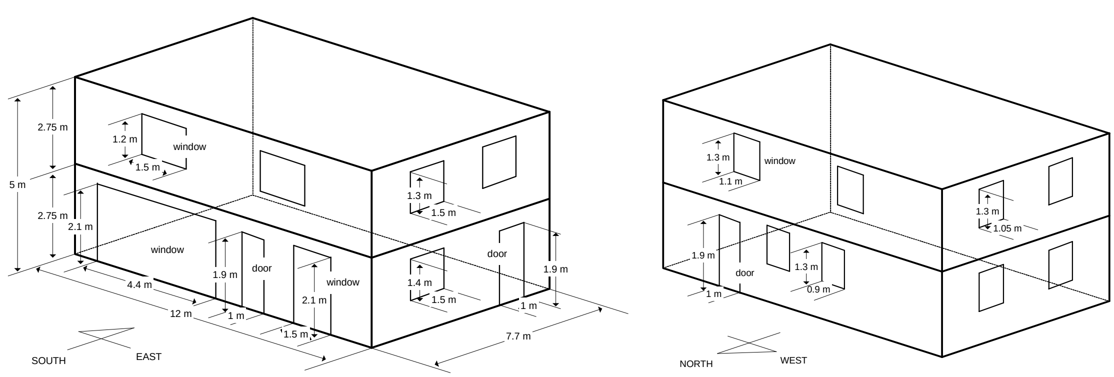

Figure 4.36 Views of a Target Building from South-East (left) and North-West (right)

4.4.2.3 Schedule

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.

4.4.2.4 Variables

Control logic was tested for diverse variables. Variables could be categorized into basecase, architectural variables, system variables, and exterior climatic variables (Table 4.5).

Basecase	Architectural Variables	System Variables	Exterior Climatic Variables
▪ Basecase	▪ Location Factor - Orientation ▪ Envelope Factors - R-values of Walls, Roof, and Windows - Window Wall Ratio	▪ Schedule Factors - Application of Setback - Change of Setpoints	▪ Change of Internal Load ▪ Change of Ventilation Rate ▪ Change of Climate Condition

Table 4.5 Variables for Computer Simulation

a. Basecase

The basecase had constant comfort ranges for temperature, humidity and PMV. Environmental control devices worked based on those constant operating ranges. The ranges were:

- Air Temperature: 20~23°C in winter, 23~26°C in summer
- Humidity: 30~45% in winter, 45~60% in summer
- PMV: -0.5~0.0 in winter, 0.0~0.5 in summer

b. Architectural Variables

Architectural variables were related to the building configuration, which is difficult to change during a building's lifetime. The purpose of the simulation of these variables was to investigate the advanced performance of proposed logic on diverse building configurations.

Orientation

Simulations on eight different orientations of target building were conducted: south, south-east, east, north-east, north, north-west, west, and south-west. The basecase was a south-facing building. Orientation was decided by the direction that the facade of largest WWR faced.

Envelope Insulation

Diverse levels of R-values of walls, roof and windows on the target building were simulated. The basecase was R19 walls, R38 roof, R 21 floor, and R3.44 windows. Simulations were parametrically conducted, so that when the R-value of one component was changed, other components' R-values were held constant. The variation of R-values was as follows (unit of R-value is for the U.S.):

- Change of R-values of Walls: R10, 15, **19**, 30, 40, 50
- Change of R-values of Roof: R10, 20, 30, **38**, 40, 50, 60, 70, 80
- Change of R-values of Windows: R1, 2, 3, **3,44**, 4, 5, 6, 7, 8, 9, 10

Window Size

Diverse WWR (window wall ratios) of the target building were parametrically simulated: 0.1, 0.15, 0.2, 0.3, 0.4, and 0.5. The basecase was 0.15 WWR, on average. When the WWR was changed, the ratio was applied equally to every facade. Table 4.6

summarizes the size of envelope components for diverse WWR. As WWR increased, the area of window increased for all directions.

WWR	South			East			North			West	
	Wall (m^2)	Window (m^2)	Door (m^2)	Wall (m^2)	Window (m^2)	Door (m^2)	Wall (m^2)	Window (m^2)	Door (m^2)	Wall (m^2)	Window (m^2)
0.1	53.44	10.66	1.9	36.45	4.00	1.9	60.63	3.47	1.9	38.71	3.64
0.15	48.11	15.99	1.9	34.45	6.00	1.9	58.90	5.20	1.9	36.89	5.46
0.2	42.78	21.32	1.9	32.45	8.00	1.9	57.17	6.93	1.9	35.07	7.28
0.3	32.12	31.98	1.9	28.45	12.00	1.9	53.70	10.40	1.9	31.43	10.92
0.4	21.46	42.64	1.9	24.45	16.00	1.9	50.23	13.87	1.9	27.79	14.56
0.5	10.80	53.3	1.9	20.45	20.00	1.9	46.80	17.30	1.9	24.15	18.20

Table 4.6 Size of Envelope Components based on WWR

<u>Internal Loads</u>

The performance of control logic was tested for a case in which internal loads would be changed during certain periods. Table 4.7 describes the internal heat and moisture gain of a day. During the 7:00~10:00 and 17:00~20:00 periods, the internal loads were assumed to be two times the basecase.

<table>
<tr><th rowspan="2">Time of Day</th><th colspan="2">Heat Gain (Watt)</th><th rowspan="2">Moisture Gain (ml)</th><th rowspan="2">Time of Day</th><th colspan="2">Heat Gain (Watt)</th><th rowspan="2">Moisture Gain (ml)</th></tr>
<tr><th>Sensible</th><th>Latent</th><th>Sensible</th><th>Latent</th></tr>
<tr><td>0-1</td><td rowspan="7">Same with the basecase</td><td rowspan="7">Same with the basecase</td><td rowspan="7">Same with the basecase</td><td>12-13</td><td rowspan="5">Same with the basecase</td><td rowspan="5">Same with the basecase</td><td rowspan="5">Same with the basecase</td></tr>
<tr><td>1-2</td><td>13-14</td></tr>
<tr><td>2-3</td><td>14-15</td></tr>
<tr><td>3-4</td><td>15-16</td></tr>
<tr><td>4-5</td><td>16-17</td></tr>
<tr><td>5-6</td><td>17-18</td><td rowspan="3">2 times of the basecase</td><td rowspan="3">2 times of the basecase</td><td rowspan="3">2 times of the basecase</td></tr>
<tr><td>6-7</td><td>18-19</td></tr>
<tr><td>7-8</td><td rowspan="3">2 times of the basecase</td><td rowspan="3">2 times of the basecase</td><td rowspan="3">2 times of the basecase</td><td>19-20</td></tr>
<tr><td>8-9</td><td>20-21</td><td rowspan="4">Same with the basecase</td><td rowspan="4">Same with the basecase</td><td rowspan="4">Same with the basecase</td></tr>
<tr><td>9-10</td><td>21-22</td></tr>
<tr><td>10-11</td><td rowspan="2">Same with the basecase</td><td rowspan="2">Same with the basecase</td><td rowspan="2">Same with the basecase</td><td>22-23</td></tr>
<tr><td>11-12</td><td>23-24</td></tr>
</table>

Table 4.7 Internal Heat and Moisture Gain Profile based on the Floor Area

Ventilation

Change of ventilation rate was applied to the simulation as disturbance. Different from the 0.3 ACH of the basecase, it was assumed to be 1.0 ACH during the 7:00~10:00 and 17:00~20:00 periods. Table 4.8 describes the change of internal loads.

Time of Day	Ventilation (ACH)	Time of Day	Ventilation (ACH)
0-1		12-13	
1-2		13-14	
2-3		14-15	Same with the basecase
3-4	Same with the basecase	15-16	
4-5		16-17	
5-6		17-18	
6-7		18-19	1.0
7-8		19-20	
8-9	1.0	20-21	
9-10		21-22	
10-11	Same with the basecase	22-23	Same with the basecase
11-12		23-24	

Table 4.8 Daily Ventilation Profile based on the Floor Area

c. Systematic Variables

Two variables relating to the system operating method were simulated for control logic: application of setback and change of setpoints.

Setback

Night- and day-time setback mode was applied for heating, cooling, humidifying, and dehumidifying systems. Figures 4.37 through 4.42 show the application of setback modes for a day. Basically, these modes were identical to those in the recommended setback mode in the proposed control logic.

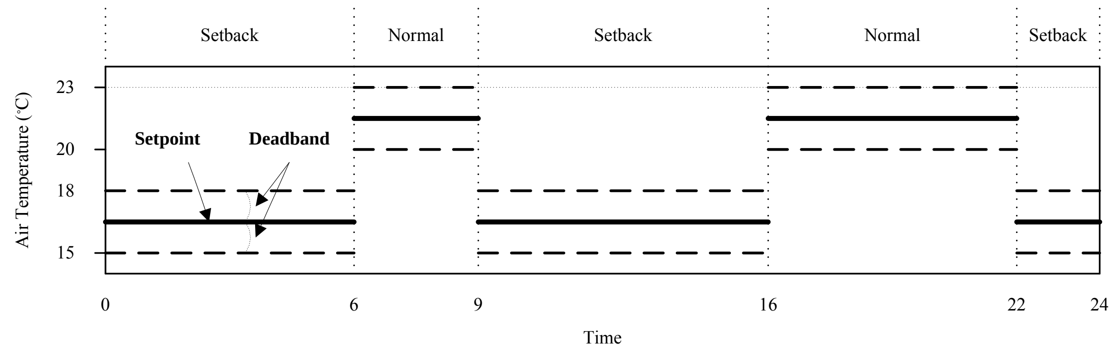

Figure 4.37 Application of Setback for Heating Systems

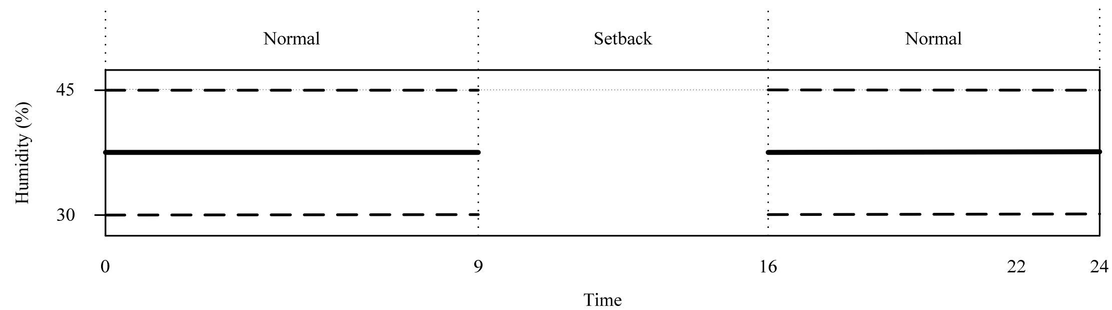

Figure 4.38 Application of Setback for Humidifying Systems

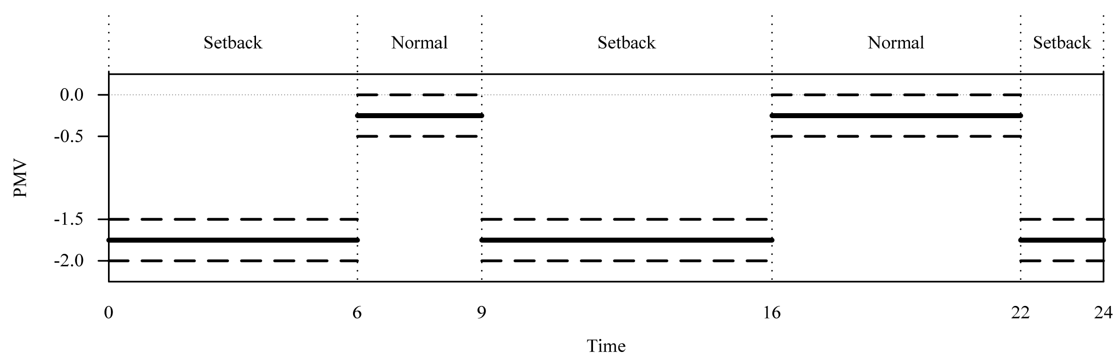

Figure 4.39 Application of Setback for PMV Increasing Systems

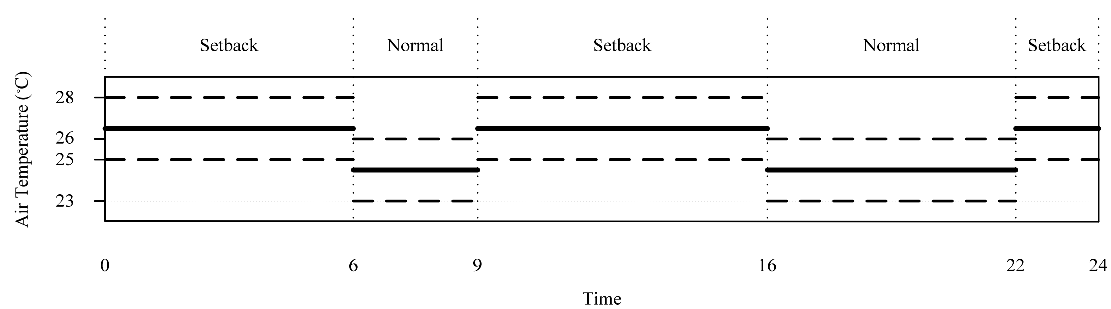

Figure 4.40 Application of Setback for Cooling Systems

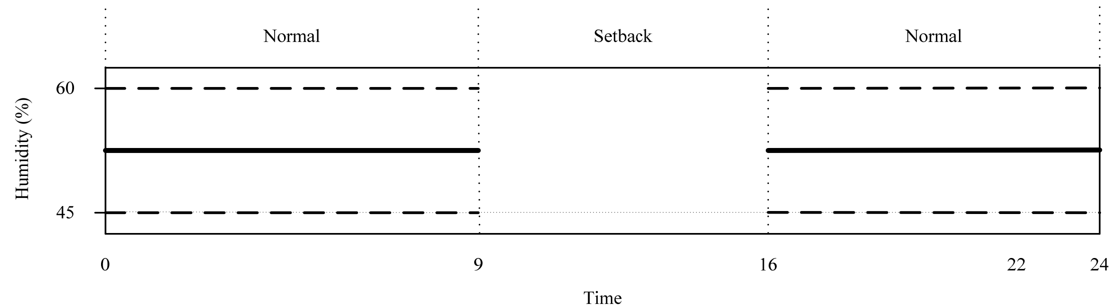

Figure 4.41 Application of Setback for Dehumidifying Systems

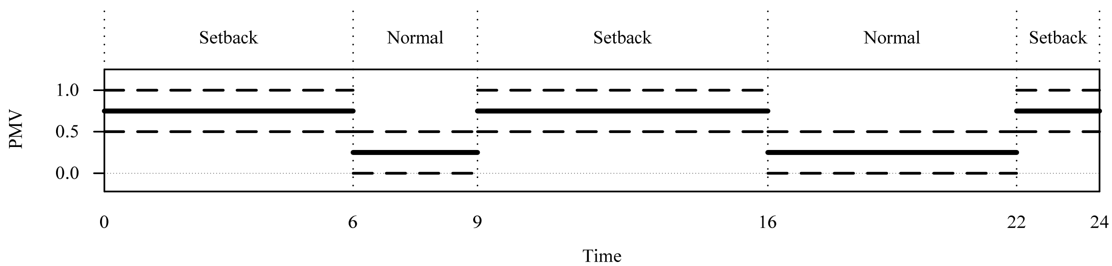

Figure 4.42 Application of Setback for PMV Decreasing Systems

Change of Setpoints

Setpoints for heating and cooling systems were parametrically simulated for the target building. In each case, the operating range for heating and cooling systems was constant once a certain setpoint was applied. The basecase was 21.5°C of a setpoint with 1.5°C of a deadband for heating systems and 24.5°C of a setpoint with 1.5°C of a deadband for cooling systems. Tested setpoints are summarized in Table 4.9.

Heating		Cooling	
Setpoint (°C)	Operating Range (°C)	Setpoint (°C)	Operating Range (°C)
16.5	15 ~ 18	21.5	20 ~ 23
17.5	16 ~ 19	22.5	21 ~ 24
18.5	17 ~ 20	23.5	22 ~ 25
19.5	18 ~ 21	24.5	23 ~ 26
20.5	19 ~ 22	25.5	24 ~ 27
21.5	20 ~ 23	26.5	25 ~ 28
22.5	21~ 24	-	-
23.5	22 ~ 25	-	-
24.5	23 ~ 26	-	-

Table 4.9 Setpoint and Operating Ranges for Heating and Cooling Systems

d. Exterior Climatic Variables

Simulations were conducted for the extreme change in weather conditions. The simulation period was composed of the heating peak day (Jan. 27 and 28) and the cooling peak (July. 7) day repeatedly. Analysis was performed for the last five days.

- Jan. 27 - Jan. 28 – July. 7 - Jan. 28 – July. 7 - Jan. 28 (6 days)

4.4.2.5 Limitations

The thermal mass effect of the building envelope could not be considered in the simulation program. Therefore, the thermal response within the building to the device operation might differ from that of actual buildings. For example, when the cooling system in the simulation was turned on during a sunny late afternoon in the summer, the indoor air temperature might decrease faster than in the actual building. That was because the heat that was stored and discharged from the envelopes and delayed the cooling effect by cooling system was not accounted for in the computer simulation. Since this effect was identically applied to all control logic, however, it might not be a significant problem when comparing the simulation results.

4.4.3 Experiment

An experiment was conducted as a secondary method to test the performance of control logic and verify the simulation results.

4.4.3.1 Control Logic

Three logics were tested: (1) temperature and humidity control without ANNs as the conventional logic, (2) temperature and humidity control with ANNs, and (3) PMV control with ANN as proposed logic.

4.4.3.2 Test Chamber

A thermal test chamber previously described in Figure 4.30 was utilized as a space for the experiment. The composition of sensor network, data acquisition system, control panel, and environmental control devices was also identical.

4.4.3.3 Schedule

Control logic was tested for two seasons—winter and summer. Five days were simulated for each case. Table 4.10 summarizes the periods of each experimental case.

		Temperature and humidity control without ANNs	Temperature and humidity control with ANNs	PMV control with ANN
Winter	Basecase	Dec.19~Dec.23, 2007	Dec.25~Dec.29, 2007	Dec.31,2007~Jan.04, 2008
	Setback	Jan.16~Jan.20, 2008	Jan.10~Jan.14, 2008	Jan.25~Jan.29, 2008
Summer	Basecase	Aug.08~Aug.12, 2008	Aug.14~Aug.18, 2008	Jun.21,~Jun.25, 2008
	Setback	Jul.18~Jul.22, 2008	Aug.20~Aug.24, 2008	Aug.02~Aug.06, 2008

Table 4.10 Schedule of Experiment

4.4.3.4 Variables

Two variables were applied: basecase and application of night- and day-time setback. The basecase had constant thermal comfort ranges for heating, cooling, humidifying, and dehumidifying devices. On the other hand, the setback mode changed the setpoint for devices for certain periods as previously described in Figures 4.37 to 4.42.

4.4.3.5 Limitations

In contrast to the computer simulation, periods for each experimental case were not identical, resulting in different weather conditions for exterior and surrounding interior spaces. Therefore, in the analysis, a period of the most similar weather conditions for each case in terms of enthalpy was sampled and the results of the experiments in those periods were compared.

4.5 Method of Data Analysis

Data analysis was conducted in three major categories: thermal comfort, features of overshoots and undershoots out of the specified comfort ranges, and energy efficiency. Features of overshoots and undershoots consisted of ratio and magnitude of overshoots and undershoots out of the specified comfort ranges.

4.5.1 Thermal Comfort

Interior air temperature, humidity, and PMV were the principal indices of thermal comfort. The percentages of comfortable period within the specified comfort ranges were calculated for comparing the thermal conditions by the conventional and proposed control logics. A control method with a higher percentage would be an advanced logic creating more comfortable thermal conditions.

4.5.2 Features of Overshoots and Undershoots out of the Specified Comfort Ranges

Ratio and magnitude of overshoots and undershoots out of the specified comfort ranges were analyzed for investigating features of shoots. First, ratio of overshoots and undershoots out of the specified comfort ranges was compared in terms of air temperature, humidity, and PMV. It was calculated by Equation 4.4. This value describes the instability of thermal conditions out of the specified comfort range by control logic.

Control logic with the lower value meant that its over- or undershoots were better stabilized within the specified comfort range.

$R = N_{shoots} / N_{total} * 100$ .... (Equation 4.4)

Where,

R: The ratio of overshoots (undershoots) out of the specified comfort range (%)

N_{shoots}: Number of overshoots (undershoots) out of the specified comfort range

N_{total}: Total number of overshoots (undershoots)

Next, the magnitude of a control system overshoots or undershoots was measured by a combination of two factors: the duration time (t) and the degree (Δ) of overshoots or undershoots. The multiplication of these two factors (t * Δ) indicated the magnitude of over- or under-shoots as in Equation 4.5. Figure 4.43 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.

$S = \sum(\Delta \times t)$ .... (Equation 4.5)

Where,

S = magnitude of overshoots or undershoots

Δ = degree of overshoots or undershoots out of the specified comfort range

t = duration time of overshoots or undershoots

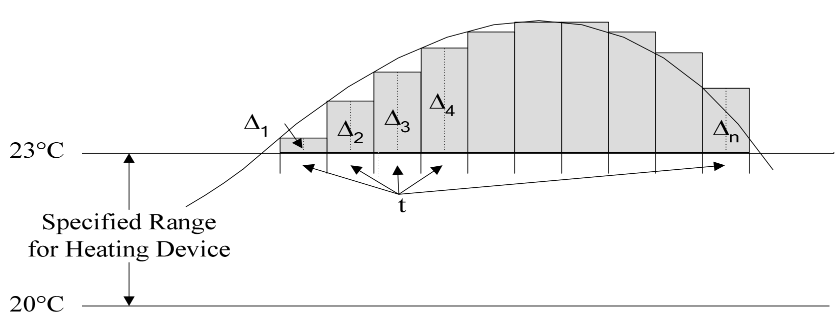

Figure 4.43 Magnitude of Overshoot of Air Temperature

4.5.3 Energy Efficiency

In the computer simulation, the amount of heat supply and removal (KWh) as well as the amount of moisture supply and removal (Kg) were calculated by the simulation tool. In the experiment, the amount of electricity consumption (Wh) of each control logic was calculated by multiplying the power required by devices and operating time. Analysis has been conducted by comparing these amounts for each control logic.

4.5 Summary

A control logic framework and four control logics, which were a conventional and three proposed logics, were developed for the thermal controls in residential buildings. In particular, among the proposed logics, two logics employed ANN models for the predictive and adaptive control. In addition, a system hardware framework was built with sensors, data acquisition system, control panel, and environmental control devices.

Computer simulation and experiment were conducted for testing the performance of developed thermal control methods. Variables represented situations that residential buildings might experience during their life span. They were composed of basecase, architectural variables, system variables, and exterior climatic variables. The first step was to compare the results by computer simulation and experiment for a simple case as a triangulation. The next step was to test control logic for diverse variables through computer simulation. And the last step was to test possible variables through experimentation.

The test results would be analyzed in terms of thermal comfort, ratio and magnitude of overshoots and undershoots out of the specified comfort ranges, and energy efficiency. Through analysis, the advanced performance of proposed methods would be proven.

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CHAPTER V

RESULTS AND DATA ANALYSES

Analyses of the results of the computer simulation and the experiment have been conducted in three phases: (1) comparison of the results from the computer simulation and the experiment, (2) the computer simulation, and (3) the experiment. The goal of the first phase was to verify the results of the computer simulation and the experiment by the comparing each air temperature profile and the amount of energy consumption. After triangular verification in the first phase, the second and third phases were conducted to test the performance of the conventional and the group of proposed control logics for the diverse situations that residential buildings can experience. Analyses were conducted for thermal comfort; features of overshoots and undershoots out of the specified comfort ranges, and energy efficiency.

5.1 Comparison of Computer Simulation and Experiment

Preliminary tests were conducted for a simple case – temperature and humidity control without ANNs. The similarity of results by the computer simulation and the experiment would support the validity of the outcomes from the main simulation and the experiment for diverse variables. The experiment was conducted on Dec. 23, 2007, and its exterior and surrounding interior weather data was utilized in the simulation. Air temperature and the amount of heat supply for this day were compared.

A profile of the interior air temperature is shown in Figure 5.1. The number of cycle (a cycle means a movement of air temperature from one starting moment of a heating device operation to the next starting moment of a heating device operation) was 17 for the simulation and 18 for the experiment. Averages of overshoots and undershoots were 0.34°C and -0.13°C for the simulation and 0.37°C and -0.31°C for the experiment. The first possible reason for different averages of overshoots and undershoots might be the discordance in the time lag effect of a heating device employed in the simulation and the experiment. In addition, other possible reasons were non-consideration of the thermal mass effect, which also causes the time lag effect, in the computer simulation; the difference in the measurement point of the air temperature (the computer simulation: homogenous in space; the experiment: center of space with 1.2m height); and potentially different ventilation rates (the computer simulation: 1.0ACH assumed; the experiment: non-measurable).

The amount of heat supplied by the heating device in the simulation and the experiment was 14.48 KWh and 14.33 KWh, respectively, as illustrated in Figure 5.2. There was a 1% increase in the simulation. This increase might be an acceptable amount based on previous studies, which noted a difference between the simulation and the experiment: a 5% difference in heat demand by J. Fredrik Karsson et al. in 2006 and a 2% difference in energy consumption by Nicolas Morel et al. [J. Fredrik Karsson et al. (2006), Nicolas Morel et al. (2001)].

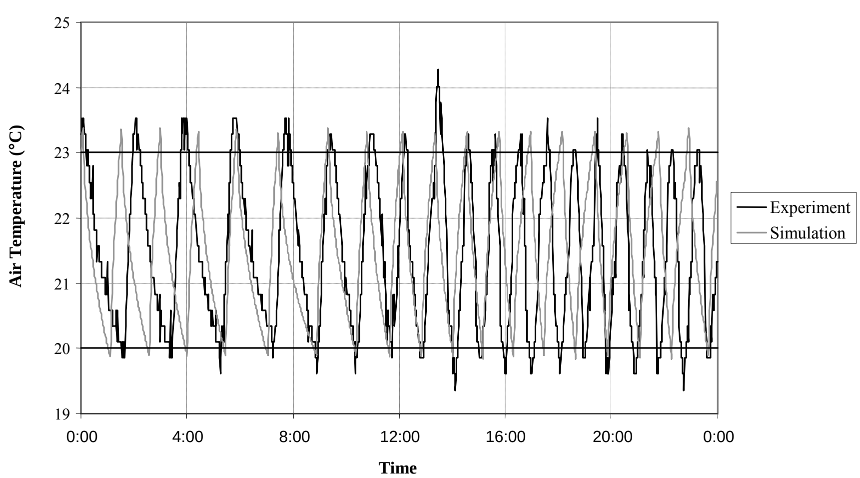

Figure 5.1 Profiles of Interior Air Temperature by the Experiment and the Simulation

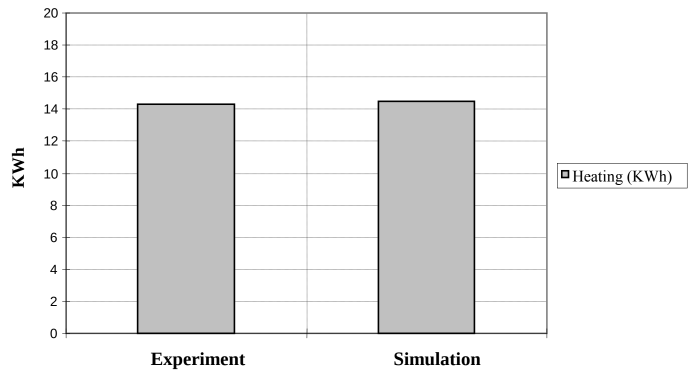

Figure 5.2 The Amount of Heat Supply by the Experiment and the Simulation

5.2 The Computer Simulation

Computer simulation was utilized as the primary method for testing the performance of the developed control logic since it can test diverse situations that cannot be manipulated in an experiment. Variables tested in the simulation were architectural variables, system variables, and exterior climatic variables.

5.2.1 Thermal Comfort

Thermal comfort by each control logic was analyzed. Three major targets to be conditioned were air temperature, humidity, and PMV.

5.2.1.1 Basecase

The comfort period over the total simulation period was summarized in terms of air temperature, humidity, and PMV (Table 5.1). Overall, ANN-based control strategies created more comfortable thermal conditions (bold numerals). Compared to the conventional logic, which was temperature and humidity control without ANNs, temperature and humidity control with ANNs improved air temperature comfort to 100.0% from 95.8% in winter and to 100.0% from 96.1% in summer. Air temperature profiles for winter and summer are compared in Figures 5.3 and 5.4, respectively. While the air temperature by the conventional logic moved widely and went out of the comfort range, that by the predictive logic was better conditioned within the comfort range. Similar to air temperature, comfort humidity periods improved slightly by the predictive logic using ANN models: to 100.0% from 99.9% in winter and to 99.9% from 99.2% in summer. Figures 5.5 and 5.6 shows humidity movement in winter and summer by two logics. Humidity fluctuation was dependent on the air temperature movement. When air temperature rose, humidity dropped. Thus, there were small scale humidity fluctuations in one large cycle of humidity movement. In both Figures, humidity were more properly conditioned using the predictive logic.

A control logic having PMV as a control variable had a larger PMV comfort period compared to control logics having air temperature and humidity as control variables. This shows the potential of the PMV-based control method in residential buildings. In addition, comfortable PMV periods improved to 98.5% from 89.5% in winter and to 79.0% from 75.1% in summer using PMV control with ANN compared to PMV control without ANN. As shown in Figures 5.7 and 5.8, PMV was conditioned better within the comfort ranges by predictive logic using ANN model. This stability is due to the reduction in overshoots and undershoots using the ANN-model-based predictive controls.

Season	Specified Comfort 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 5.1 Comparison of Air Temperature, Humidity, and PMV Comfort Period (%): Basecase

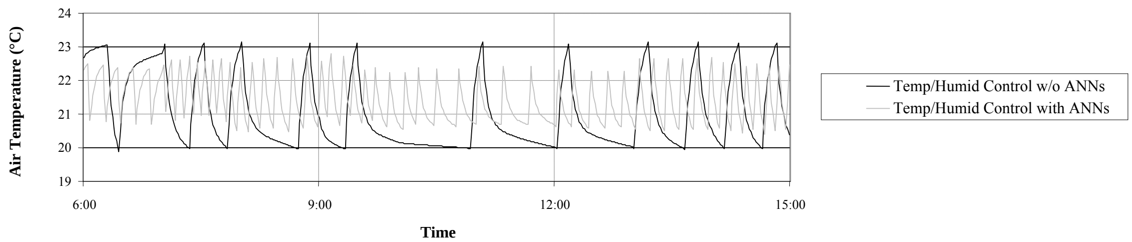

Figure 5.3 Air Temperature Profiles of Two Control Logics (Temperature and Humidity Control without ANNs and Temperaturea and Humidity Control with ANNs) Using a Heating Device in Winter (6:00~15:00 on Jan. 30, 2007)

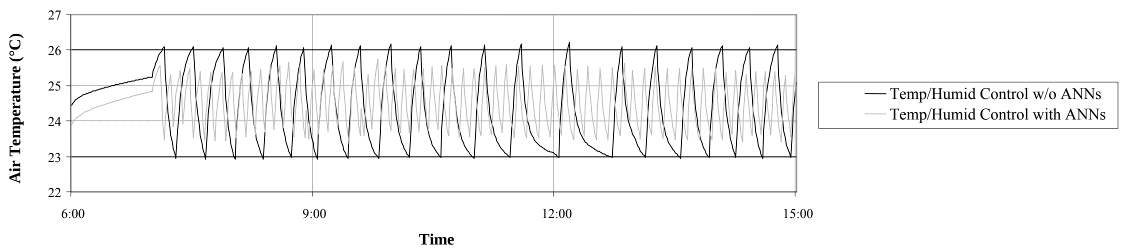

Figure 5.4 Air Temperature Profiles of Two Control Logics (Temperature and Humidity Control without ANNs and Temperaturea and Humidity Control with ANNs) Using a Cooling Device in Summer (6:00~15:00 on Jul. 06, 2007)

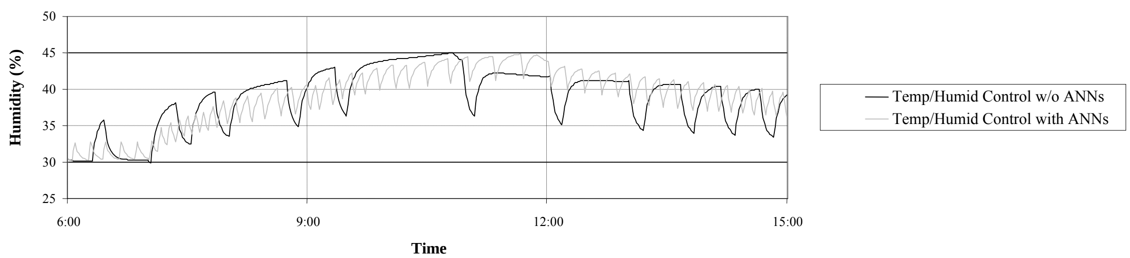

Figure 5.5 Humidity Profiles of Two Control Logics (Temperature and Humidity Control without ANNs and Temperaturea and Humidity Control with ANNs) Using a Humidifying Device in Winter (6:00~15:00 on Jan. 30, 2007)

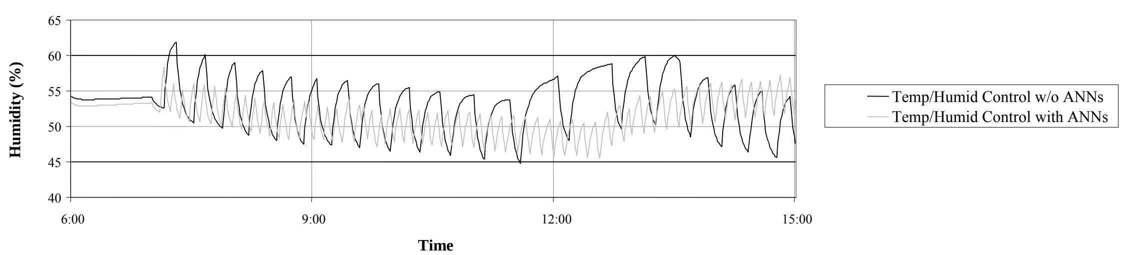

Figure 5.6 Humidity Profiles of Two Control Logics (Temperature and Humidity Control without ANNs and Temperaturea and Humidity Control with ANNs) Using a Dehumidifying Device in Summer (6:00~15:00 on Jul. 06, 2007)

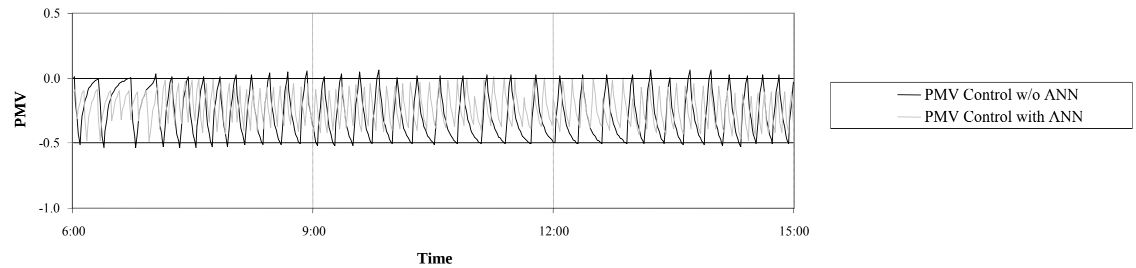

Figure 5.7 PMV Profiles of Two Control Logics (PMV Control without ANN and PMV Control with ANN) Using Heating and Humidifying Devices in Winter (6:00~15:00 on Jan. 30, 2007)

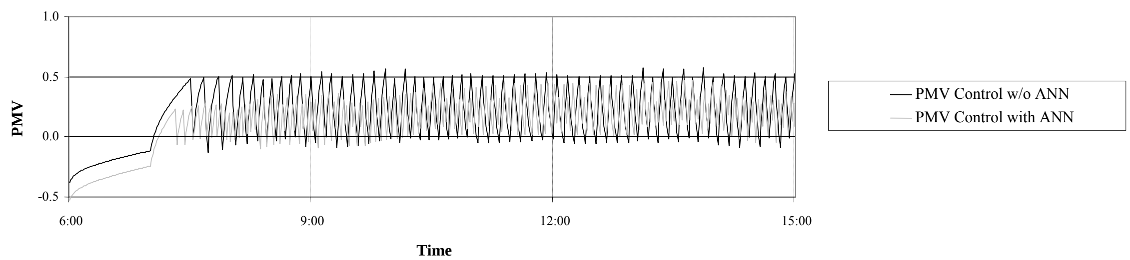

Figure 5.8 PMV Profiles of Two Control Logics (PMV Control without ANN and PMV Control with ANN) Using Cooling and Dehumidifying Devices in Summer (6:00~15:00 on Jul. 06, 2007)

5.2.2.2 Architectural Variables

The thermal comfort period was parametrically analyzed for the architectural variables: orientation, R-value for walls, the roof and windows, and window wall ratio (WWR).

a. Orientation

For all eight orientations in both seasons, the percentage of the comfort periods of air temperature using temperature and humidity control with ANNs were higher than those of conventional logic (Figure 5.9). The amount of improvement varied from 2.7% (North-East) to 5.2% (North) in winter and from 3.9% (South, South-East, and North-West) to 4.2% (East, North, and West) in summer.

For all directions, the percentage of the comfort periods of humidity was similar or slightly improved by the predictive logic with ANNs (Figure 5.10). The maximum amount of improvement was 0.1% in winter and 0.8% in summer. The effect of ANN application was less significant for humidity control, presumably because the time lag with a humidifying device and the building response were smaller than that of air temperature.

The percentage of the comfort periods of PMV using PMV control with ANN were higher than the PMV control without ANN in both seasons (Figure 5.11). The amount of improvement ranged from 3.3% (South) to 11.0% (East) in winter and from 1.4% (North-West) to 9.9% (West) in summer. The lower percentage of the comfort periods in summer compared to winter was because PMV went below under the specified comfort range during the night-time and early morning even though the devices for decreasing PMV such as cooling or dehumidifying did not operate during those periods.

The amount of improvement in PMV control was larger than those in air temperature and humidity controls. There are two major reasons for this. The first reason is the magnification of overshoots and undershoots when PMV is controlled. For controlling PMV, two devices for controlling air temperature and humidity worked simultaneously. For example in winter, PMV increased by operations of heating and humiditying devices. When PMV went over the comfort range, both devices stopped working. At this moment, there were two overshoot factors: air temperature and humidity. PMV overshoot was calculated using these two overshoots, thus the amount of PMV overshoot was magnified. The predictive control logic removed this magnified overshoot. Therefore, the amount of improvement was more significant in PMV control than air temperature or humidity control.

The second reason is the narrower comfort range for PMV. For example in winter, the specified comfort range of PMV was -0.5~0.0 (ΔPMV=0.5). That of air temperature was 20~23°C (Δair temperature=3.0°C). If Δair temperature (3.0°C) is converted in PMV, it is 0.8247 (assuming that humidity is 37.5%, MRT is same with air temperature, air velocity is 0.0m/s, 1.0 CLO, and 1.0 MET). In this way, since PMV had a narrower comfort range, the frequency of device on and off was higher resulting in the increased total amount of overshoots and undershoots. Therefore, the improvement of comfort period using the predictive logic, which aimed to reduce overshoots and undershoots, was more significant in PMV control.

From a comparison of the comfort periods of air temperature, humidity, and PMV, it can be concluded that the logic with the ANN models improves the thermal conditions of buildings for all directions.

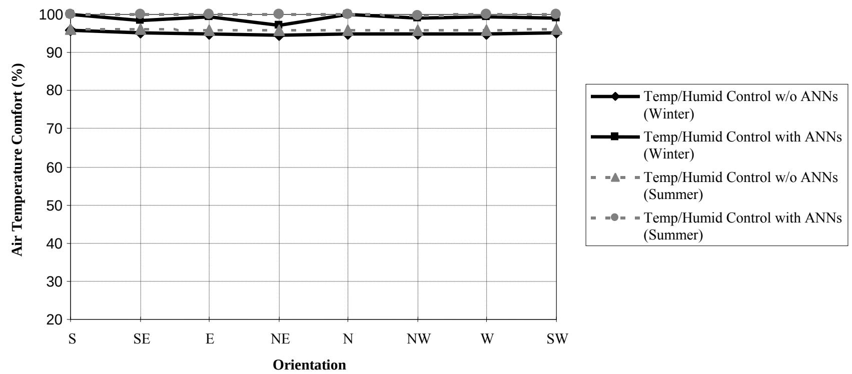

Figure 5.9 Comparison of Air Temperature Comfort Period (%): Orientation

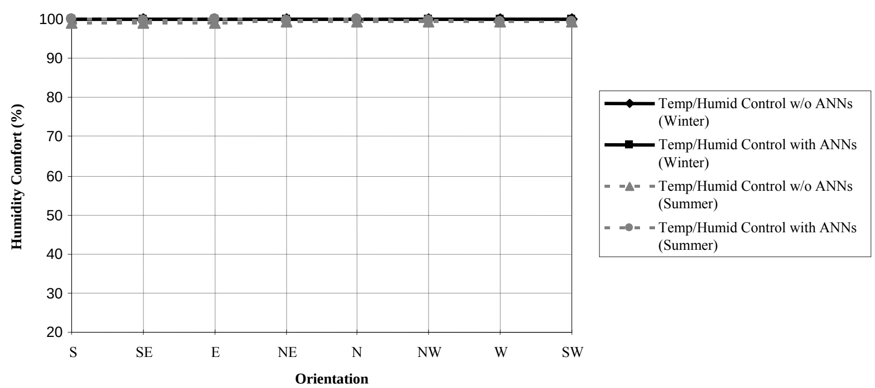

Figure 5.10 Comparison of Humidity Comfort Period (%): Orientation

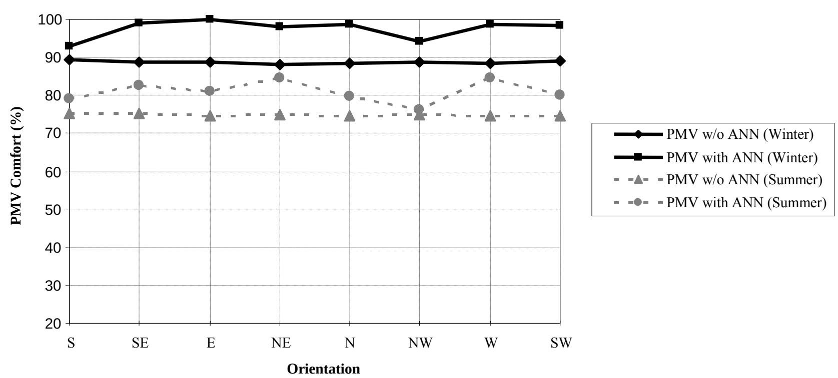

Figure 5.11 Comparison of PMV Comfort Period (%): Orientation

b. R-values for Walls

Control logics were tested parametrically from R10 to R50 walls. In winter, the comfort period of air temperature increased up to R19 and was then stablized (Figure 5.12), thus indicating that super insulation over R19 walls is not significantly beneficial in terms of the comfort periods. For all degrees of R-values, the comfort periods using the logic with the ANN models was larger than that of the conventional logic. Similarly, in summer, the predictive logic with ANNs controlled air temperature more comfortably for all R-values. The amount of improvement varied from 2.5% (R10) to 4.7% (R50) in winter and from 1.1% (R10) to 4.1% (R30) in summer. These results indicate that air temperature is controlled better by the logic with the ANN model for the diverse R-values for walls.

The percentage of the comfort periods for humidity using both control logics was close to 100.0% in winter and summer (Figure 5.13), which means that the interior humidity is properly controlled using the conventional logic as well.

The comfort period of PMV increased with higher R-values up to R19 and then became stabilized (Figure 5.14). For both seasons, PMV control with ANN conditioned PMV more comfortably than PMV control without ANN. The amount of improvement ranged from 5.8% (R10) to 11.7% (R30) in winter and from 1.5% (50) to 10.3% (R30) in summer. It can be concluded that PMV control with the ANN model can improve the PMV conditions for the diverse R-values for walls.

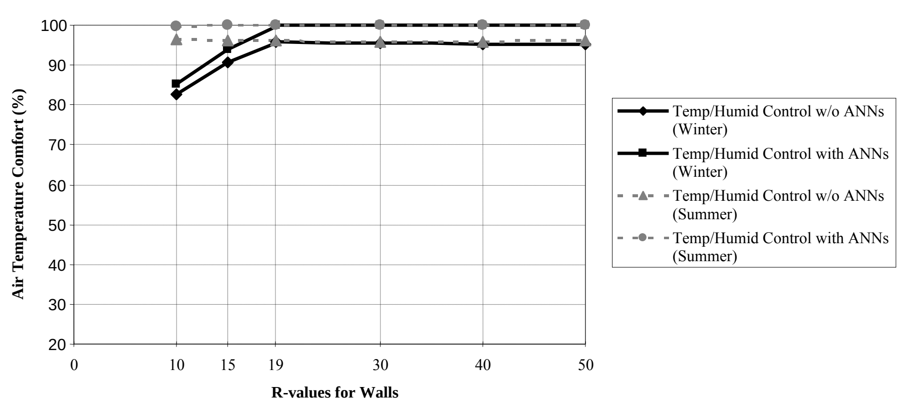

Figure 5.12 Comparison of Air Temperature Comfort Period (%): R-values for Walls

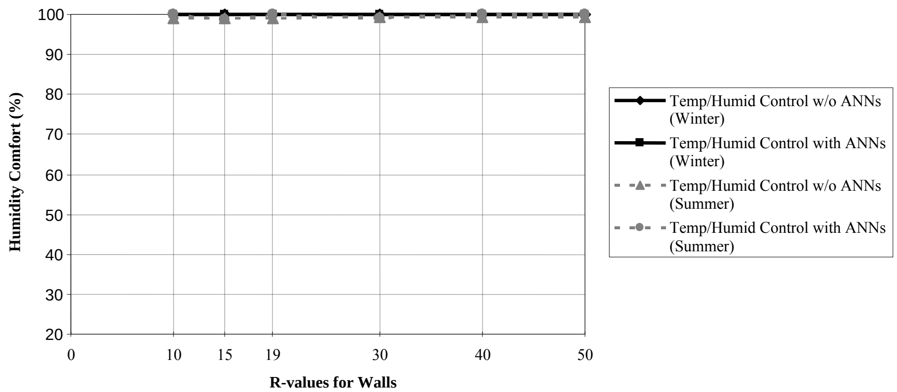

Figure 5.13 Comparison of Humidity Comfort Period (%): R-values for Walls

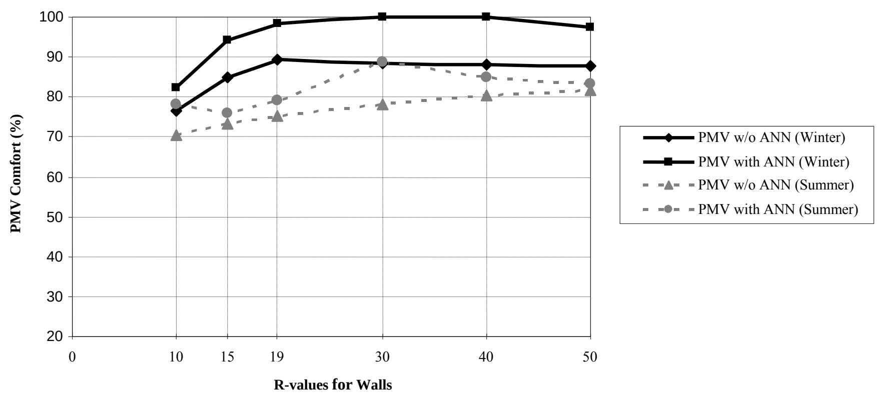

Figure 5.14 Comparison of PMV Comfort Period (%): R-values for Walls

c. R-values for the Roof

Control logics were tested from an R10 to R80 roof. The comfort period for air temperature increased up to around R38, which means that insulation over R38 roof is not significantly beneficial in terms of the comfort periods (Figure 5.15). For all R-values, the predictive logic with the ANN models conditioned air temperature better than the conventional logic. The amount of improvement using the predictive logic ranged from 2.7% (R10) to 7.1% (R30) in winter and from 3.5% (R10) to 3.9% (R30, 38 and 50~80) in summer. Therefore, it can be concluded that the ANN-based predictive control logic improves air temperature conditions for diverse R-values for the roof.

The percentage of the comfort periods for humidity was similarly close to 100.0% for both the conventional and the predictive logic with ANNs (Figure 5.16), which indicates that the conventional logic controls humidity well enough in terms of comfort.

Similar to the air temperature, the comfort period did not increase after around R38 (Figure 5.17). Periods of comfortable PMV were improved in both seasons using PMV control with the ANN model, as shown in Figure 5.11. The improvements were from 7.3% (R10) to 11.0% (R80) in winter and from 3.3% (R50) to 7.3% (R20) in summer. Based on the comparison, it is shown that the predictive PMV control logic is advantageous for regulating the PMV conditions for the diverse R-values of the roof.

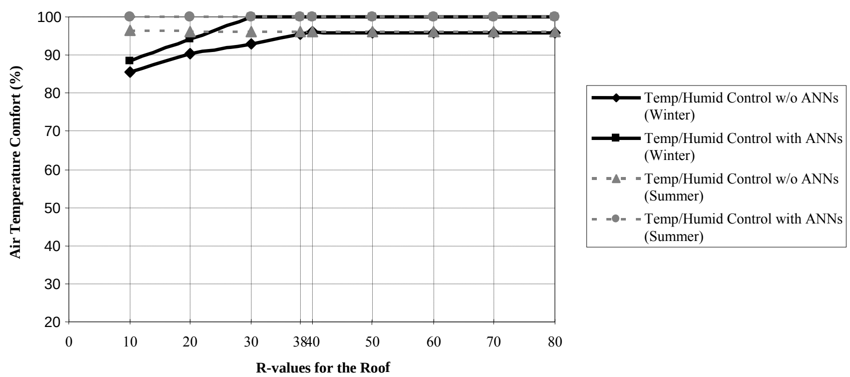

Figure 5.15 Comparison of Air Temperature Comfort Period (%): R-values for the roof

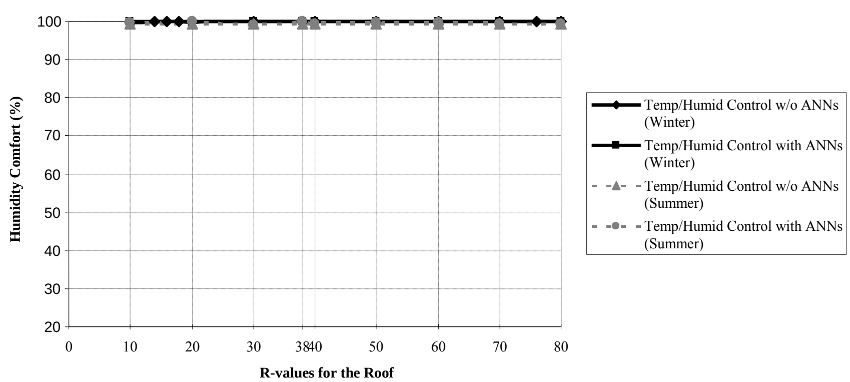

Figure 5.16 Comparison of Humidity Comfort Period (%): R-values for the roof

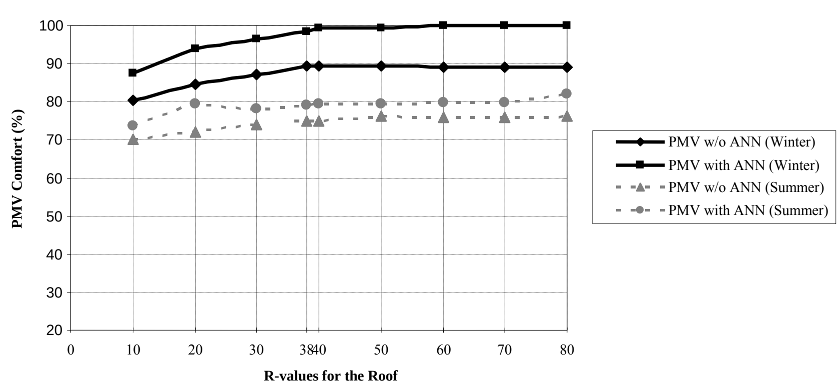

Figure 5.17 Comparison of PMV Comfort Period (%): R-values for the roof

d. R-values for Windows

Control logics were tested from R1 to R10 windows. The comfort period of air temperature increased up to around R3.44, after which it stabilized (Figure 5.18). Thus, R-values over 3.44 or so are not significantly beneficial in terms of the comfort periods. For all R-values, the comfort periods using the predictive logic with ANNs was larger than those of the conventional logic in both seasons. The amount of improvement went from 1.1% (R1) to 6.3% (R3.44) in winter and from 1.7% (R1) to 4.1% (R8, 9) in summer. This improvement supports the advantages of the ANN model for the diverse R-values for windows.

Similar to the R-values for walls and the roof, the percentage of comfort humidity using the conventional and the predicted logic with ANNs was close to 100.0% (Figure 5.19), which means that both of the control logics control humidity conditions properly.

In addition, the percentage of comfort PMV periods increased with higher R-values up to R3.44 (Figure 5.20). One noticeable point is that the comfort period did not increase significantly and even decreased in higher R-vaule cases. From the R3.44 and higher cases, the capacities of heating and humidifying devices were enough to maintaining PMV comfortably without dropping PMV down to the comfort range even during the coldest period. Therefore, the amount of comfort period was a matter of overshoots and undershoots. This fact could cause the reduction of comfort period in higher R-value cases. For example, using PMV control with ANN logic in winter, the comfort period decreased in R4 case compared to R3.44 case. It was because that in R4 case, undershoots out of comfort range were more significant than R3.44 case during the early simulation period (Day1), which, however, decreased after Day2. Similar phenomenon occurred in R6 case using PMV control with ANN in summer. However, in any cases, the amounts of comfort period were increased by the predictive control of PMV with ANN compared to the PMV control without ANN. The amount of improvement went from 3.8% (R1) to 12.4% (R9, 10) in winter and from 1.1% (R6) to 7.3% (R2) in summer. Predictive control with the ANN model could be concluded to be more effective logic for controlling PMV for the diverse R-values for windows.

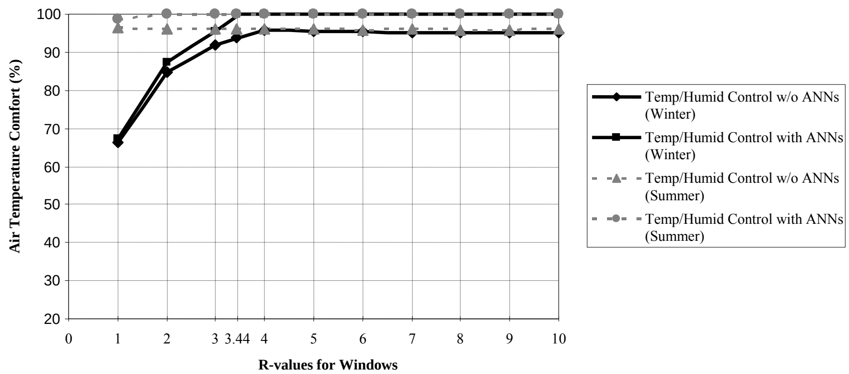

Figure 5.18 Comparison of Air Temperature Comfort Period (%): R-values for Windows

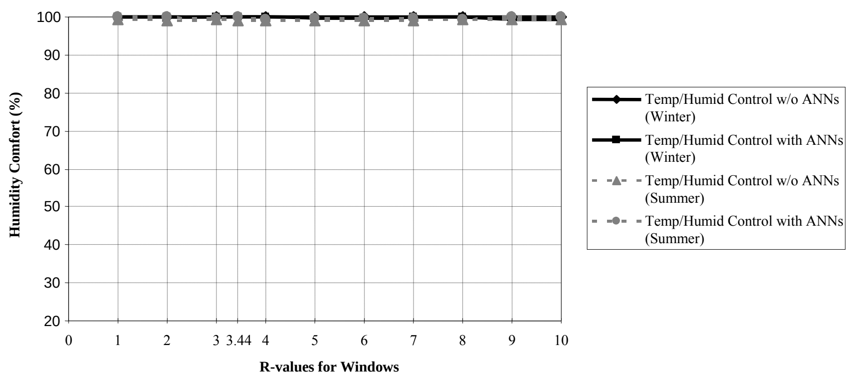

Figure 5.19 Comparison of Humidity Comfort Period (%): R-values for Windows

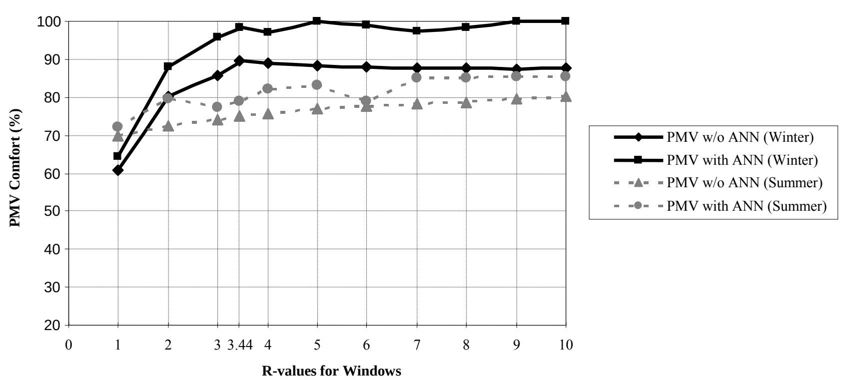

Figure 5.20 Comparison of PMV Comfort Period (%): R-values for Windows

e. Window Wall Ratio

Control logics were tested parametrically from 0.1 to 0.5 Window Wall Ratios (WWR). In both seasons, the comfort period for air temperature decreased as WWR increased, and beginning to decrease rapidly at around WWR 0.15 (Figure 5.21). This decrease meant that the heating and cooling devices equipped in this study were not able to condition the air temperature comfortably when there was excessive heat loss and gain through the windows in high WWR cases.

While the predictive logic improved air temperature conditions significantly in low WWR cases, the percentage of the comfort periods approached that of the conventional logic as the WWR increased. This similarity was due to the reduction in the number of on/off signals for control devices in higher WWR cases. For example, a heating device was apt to continue working continuously because of the larger heat loss through the envelope in high WWR buildings. Therefore, on/off frequency was smaller than that of lower WWR cases. This phenomenon, thus, decreased the positive effect expected by the ANN-based logic, which would have increased the comfort period by reducing overshoots and undershoots at the moment the device was turning on or off. Therefore, the amounts of improvement were from 0.0% (WWR0.4) to 4.2% (WWR0.15) in winter and from 0.0% (WWR0.5) to 4.2% (WWR0.1) in summer. One exceptional case occurred with in WWR0.4 in summer, in which the predictive logic decreased the comfort percentage by 0.3%. This decrease was due to the unnecessary operation of A/C in the early period of the simulation (first and second day of the simulation). In this case, the ANN model predicted the future air temperature incorrectly. However, as the ANN model was trained, this phenomenon no longer occurred after day three (Figure 5.22).

The percentage of comfort humidity was similar with both the conventional logic and the predictive logic (Figure 5.23), which means that the predictive logic did not significantly improve the humidity conditions . For both logics, the percentage of comfort period in high WWR in winter dropped because the interior humidity was maintained higher (>45%) out of the specified comfort range (30~45%), even without the operation of a humidifying device. This high humidity was due to the cold interior air temperature of high WWR cases, such as 0.4 and 0.5, in which the humidity level rose symmetrically.

There was an exceptional case that the predictive logic decreased the comfortable humidity period (WWR0.2 in summer) because of the unnecessary dehumidifying operations in Figure 5.24. It was also due to insufficient training resulting in inaccurate predictions. In particular, the number of device on and off for humidity control was much smaller (e.g., 2 times for whole period) than those for temperature control. Therefore, the ANN model could not have enough training process using new data sets.

The comfort period of PMV showed a similar pattern for air temperature (Figure 5.25). In both seasons, the comfort period of PMV decreased as the WWR increased, and also began to decrease rapidly beginning at around WWR 0.15. In addition, while the ANN-based logic improved the PMV conditions in both seasons, the amount of improvement was reduced in higher WWR cases. Both phenomena were due to the same reasons as in the air temperature case. Thus, the amount of improvement ranged from 0.0% (WWR0.4) to 10.1% (WWR0.1) in winter and from 2.0% (WWR0.3) to 8.6% (WWR0.1) in summer. One exceptional case occurred in WWR0.5 in summer, in which the PMV control with ANN decreased the comfort percentage by 0.3% (Figure 5.26). This decrease was due to the non-operation of A/C and the dehumidifier in the early period of the simulation (second day of the simulation). The ANN model predicted the future PMV incorrectly in this case, but this phenomenon no longer occurred after day three after sufficient training.

From this result, the future control logic needs to have additional functions for preventing these improper operations. For example, cooling devices is turned on when current air temperature is higher than the specified comfort range even though the summation of current air temperature and predicted temperature is within the specified comfort range. In addition, cooling devices is turned off when current air temperature is lower than the specified comfort range even though the summation of current air temperature and predicted temperature is within the specified comfort range. This counterplan also needs to be applied to not only the heating devices, but also to the humidity and PMV control devices in a similar way.

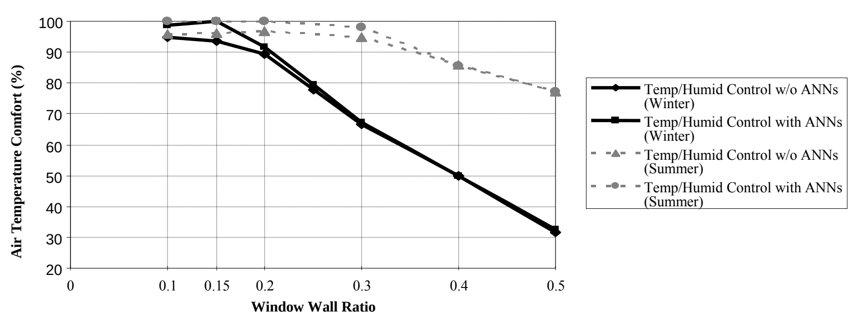

Figure 5.21 Comparison of Air Temperature Comfort Period (%): Window Wall Ratio

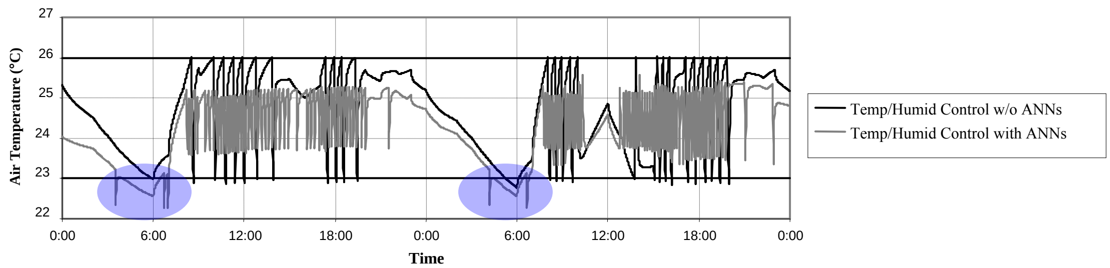

Figure 5.22 An Exceptional Case for Air Temperature Control: WWR 0.4 in Summer

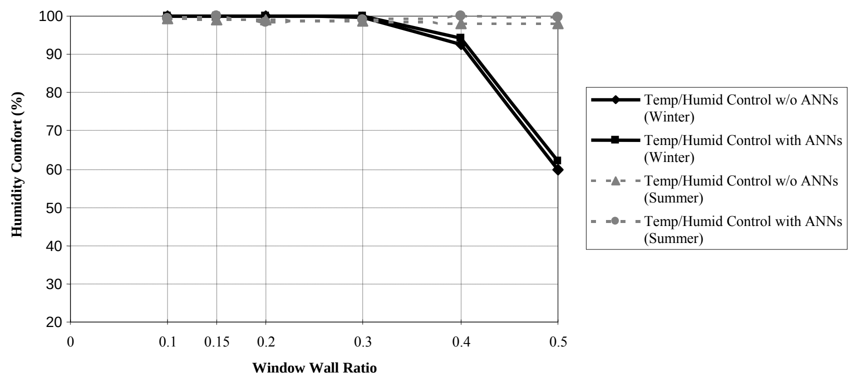

Figure 5.23 Comparison of Humidity Comfort Period (%): Window Wall Ratio

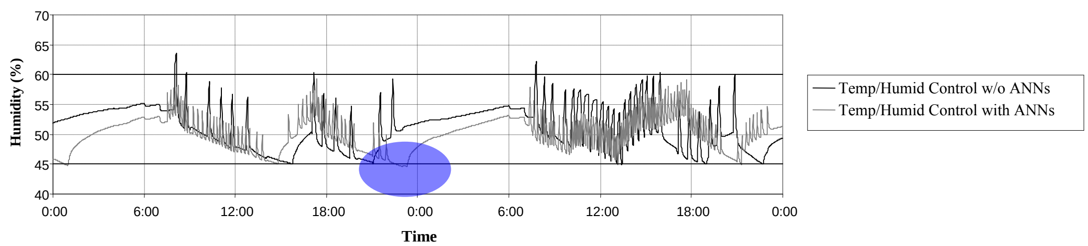

Figure 5.24 An Exceptional Case for Humidity: WWR 0.2 in Summer

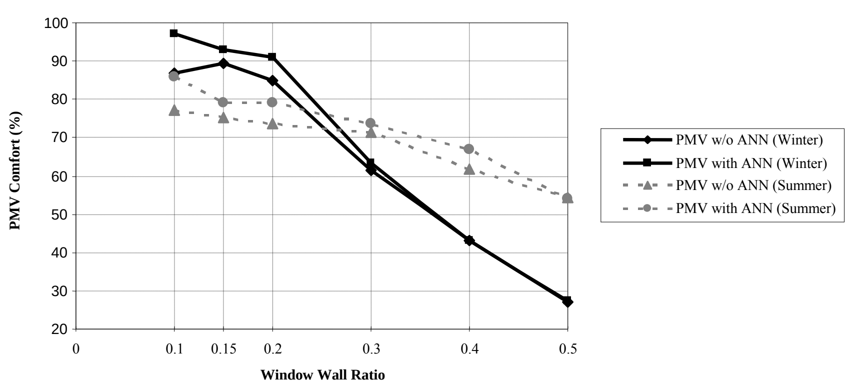

Figure 5.25 Comparison of PMV Comfort Period (%): Window Wall Ratio

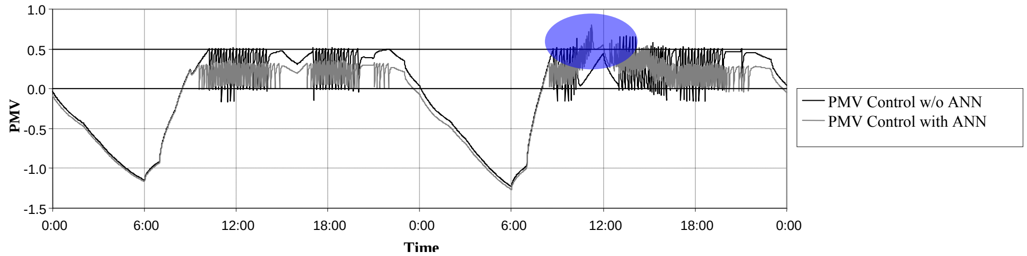

Figure 5.26 An Exceptional Case for PMV Control: WWR 0.5 in Summer

f. Change in Internal Load

Control logics were simulated for the case of increased internal load in the morning (7~10 am) and evening (17~20 pm), twice as much as the basecase. The comfort period for air temperature improved to 97.6% from 94.9% in winter and to 100.0% from 96.3% in summer. Humidity also advanced—to 100.0% from 99.0% in winter, and to 100.0% from 99.3% in summer—using the predictive control logic. In addition, the comfort period for PMV improved to 98.4% from 88.8% in winter and to 78.5% from 74.1% in summer using PMV control with ANN (Table 5.2). Accordingly, the predictive control logics better controlled the environments with an abnormal change of internal load.

Season	Specified Comfort 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)	94.9	**97.6**	80.2	98.5
	Humidity (30~45%)	99.0	**100.0**	0.0	0.0
	PMV (-0.5~0.0)	55.3	49.2	88.8	**98.4**
Summer	Air Temperature (23~26˚C)	96.3	**100.0**	36.7	49.6
	Humidity (45~60%)	99.3	**100.0**	29.8	17.9
	PMV (0.0~0.5)	4.9	0.0	74.1	**78.5**

Table 5.2 Comparison of Air Temperature, Humidity, and PMV Comfort Period (%): Change of Internal Load

g. Change in Ventilation Rate

Simulations were conducted for increased ventilation rate (1.0 ACH) in the morning (between 7~10 am) and evening (17~20 pm). The basecase was a constant rate (0.3 ACH) for the entire day. Compared to the logic without ANN, the ANN-based logic for temperature and humidity control improved thermal comfort (Table 5.3). Air temperature improved to 88.8% from 85.1% in winter and to 100.0% from 96.3% in summer; humidity advanced to 100.0% from 99.7% in winter and to 98.6% from 94.8% in summer. In addition, PMV improved to 86.7% from 79.8% in winter and to 80.9% from 75.0% in summer using PMV control with ANN. Thus, the predictive logics with ANN models can be seen to work better in an environment with a change in ventilation rate.

Season	Specified Comfort 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)	85.1	**88.8**	66.1	94.5
	Humidity (30~45%)	99.7	**100.0**	63.6	62.6
	PMV (-0.5~0.0)	47.9	40.4	79.8	**86.7**
Summer	Air Temperature (23~26˚C)	96.3	**100.0**	32.8	39.2
	Humidity (45~60%)	94.8	**98.6**	57.9	46.3
	PMV (0.0~0.5)	6.6	0.0	75.0	**80.9**

Table 5.3 Comparison of Air Temperature, Humidity, and PMV Comfort Period (%): Change of Ventilation Rate

5.2.1.3 System Variables

The thermal comfort period with the control logics were investigated for the application of setback (night- and day-time setback for control devices) and change of setpoint for the heating and cooling devices.

a. Application of Setback

Compared to the logic without the ANN models, the ANN-based predictive logic improved thermal comfort in terms of air temperature, humidity, and PMV in both seasons (Table 5.4). Overall air temperature improved to 76.1% from 73.5% in winter and to 86.4% from 83.8% in summer. Humidity advanced to 99.3% from 98.5% in winter and to 96.9% from 94.3% in summer. In addition, PMV improved to 68.7% from 61.9% in winter and to 68.3% from 61.9% in summer. The comfort period of each specified comfort range—normal and setback— improved with the predictive logic. These results indicate that thermal conditions is controlled better using the logic with the ANN model for the application of setback mode for control devices.

Season	Specified Comfort 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	49.7	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**

Table 5.4 Comparison of Air Temperature, Humidity, and PMV Comfort Period (%): Application of Setback

b. Change of Setpoint

The setpoint for the heating and cooling devices was parametrically simulated. The predictive logic improved the air temperature comfort for all setpoints in both seasons (Figure 5.27). The amount of improvement went from 1.5% (setpoint 22.5°C) to 4.4% (setpoint 18.5°C) in winter and from 2.0% (setpoint 25.5 and 26.5°C) to 4.5%

(setpoint 22.5°C) in summer, meaning that the ANN model was advantageous for diverse degrees of setpoint.

The conventional and the predictive logics created a similar humidity comfort conditions, with the exception for setpoint 16.5°C in winter (Figure 5.28). In this case, the lower air temperature around or below 15°C using the conventional method caused the higher humidity conditions to go out of the specified comfort range (>45%). Therefore, the difference in the comfortable humidity period was larger compared to what it was at other setpoints. At other setpoints, the humidity level was better maintained within the the specified comfort range. The amount of improvement went from 0.0% (setpoint 18.5, 19.5, and 20.5°C) to 11.6% (setpoint 16.5°C) in winter and from 0.4% (setpoint 25.5°C) to 0.8% (setpoint 26.5°C) in summer, meaning that the ANN model was advantageous for diverse degrees of setpoint. It can be concluded that both the conventional and predictive logic can control the humidity level well enough unless the air temperature setpoint is too low (e.g., 16.5°C).

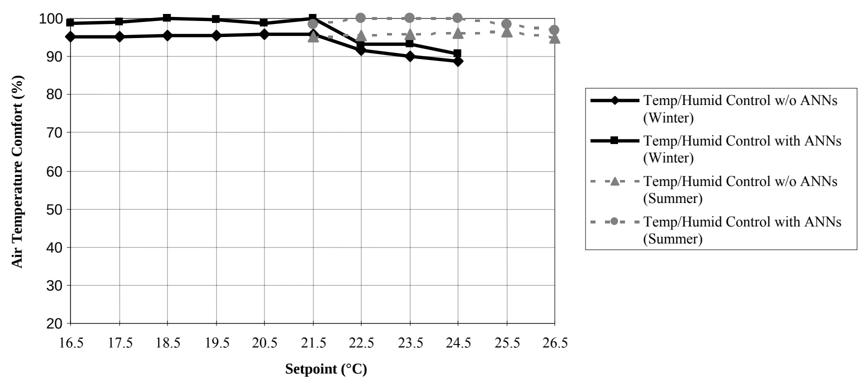

Figure 5.27 Comparison of Air Temperature Comfort Period (%): Change of Setpoint

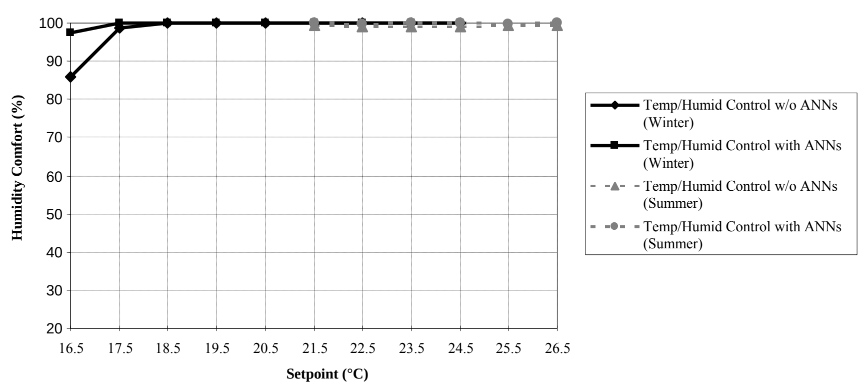

Figure 5.28 Comparison of Humidity Comfort Period (%): Change of Setpoint

5.2.1.4 Exterior Climate Variables

Simulations were conducted for an extreme change in climate conditions. The logic with the ANN model improved thermal comfort (Table 5.5). Air temperature slightly improved to 98.7% from 98.6% and humidity advanced to 94.7% from 91.7% using temperature and humidity control with ANNs. In addition, PMV improved to 98.8% from 96.3% using PMV control with ANN. These improvements demonstrated the effect of predictive control with the ANN models.

Specified Comfort Ranges	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs	PMV Control w/o ANN	PMV Control with ANN
Air Temperature (20~23°C for heating and 23~26°C for cooling)	98.6	**98.7**	79.3	99.2
Humidity (30~45% for humidifying and 45~60% for dehumidifying)	91.7	**94.7**	28.2	28.6
PMV (-0.5~0.0 for PMV increasing and 0.0~0.5 for PMV deceasing)	52.2	31.9	96.3	**98.8**

Table 5.5 Comparison of Air Temperature, Humidity, and PMV Comfort Period (%): Change of Climate Conditions

5.2.2 Features of Overshoots and Undershoots out of the Specified Comfort Ranges

Features of overshoots and undershoots for air temperature, humidity, and PMV by the operation of control devices were analyzed. The contents analyzed were the ratio of overshoots and undershoots out of the specified comfort ranges (%), and the magnitude of overshoots and undershoots out of the specified comfort ranges (˚C*minutes, %*minutes, and PMV*minutes). Through a comparison of ratio and magnitude, the stability of thermal comfort factors for each control logic was investigated.

5.2.2.1 Basecase

The ratios of overshoots and undershoots for air temperature out of the specified comfort range were all 100.0% using the conventional logic, which meant that every shoot went out of the specified comfort range. In contrast, the ratios using temperature and humidity control with ANNs (the predictive logic) were all zero (Table 5.6), which means that shoots using the predictive logic did not break the boundary and always stayed comfortable. Therefore, magnitudes of shoots using the predictive logic were all 0.0 (Table 5.7). On the other hand, the magnitude of overshoots and undershoots using the conventional logic demonstrated the discomfort of air temperature resulting from the heating and cooling operations. These results indicate that the logic with the ANN model improved the stability of air temperature within the specified comfort range for the basecase.

As with the air temperature, the ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0%, while the ratios using the predictive logic were significantly reduced to 0.0% ~ 22.2% (Table 5.8). In addition, magnitudes of shoots were all significantly reduced by the predictive logic (Table 5.9). Therefore, the ANN-based control logic can be seen to control the humidity conditions more effectively within the specified comfort range.

For PMV, compared to the ratios using the logic without ANN, which were all 100.0%, the ratios using the predictive logic with the ANN model were significantly improved to 0.0 ~ 19.8% (Table 5.10). In addition, magnitudes of shoots were also reduced using the predictive logic (Table 5.11). It can thus be concluded that PMV was also better controlled by the logic with the ANN model.

System Operation	Ratio of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating (Winter)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**0.0**
Cooling (Summer)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**0.0**

Table 5.6 Ratio (%) of Overshoots and undershoots out of the Specified Comfort Range: Air Temperature, Basecase

System Operation	Magnitude of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating (Winter)	Magnitude of Overshoots (˚C*minutes)	3.96	**0.00**
	Magnitude of Undershoots (˚C*minutes)	-6.10	**0.00**
Cooling (Summer)	Magnitude of Overshoots (˚C*minutes)	5.41	**0.00**
	Magnitude of Undershoots (˚C*minutes)	-7.07	**0.00**

Table 5.7 Magnitude (˚C*minutes) of Overshoots and undershoots out of the Specified Comfort Range: Air Temperature, Basecase

System Operation	Ratio of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Humidifying (Winter)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**0.0**
Dehumidifying (Summer)	Ratio of Overshoots (%)	100.0	**10.0**
	Ratio of Undershoots (%)	100.0	**22.2**

Table 5.8 Ratio (%) of Overshoots and undershoots out of the Specified Comfort Range: Humidity, Basecase

System Operation	Magnitude of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Humidifying (Winter)	Magnitude of Overshoots (%*minutes)	0.19	**0.00**
	Magnitude of Undershoots (%*minutes)	-0.11	**0.00**
Dehumidifying (Summer)	Magnitude of Overshoots (%*minutes)	31.67	**0.22**
	Magnitude of Undershoots (%*minutes)	-1.10	**-0.21**

Table 5.9 Magnitude (%*minutes) of Overshoots and undershoots out of the Specified Comfort Range: Humidity, Basecase

System Operation	Ratio of Shoots	PMV Control w/o ANN	PMV Control with ANN
PMV Increasing (Heating and Humidifying in Winter)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**6.0**
PMV Decreasing (Cooling and Dehumidifying in Summer)	Ratio of Overshoots (%)	100.0	**5.6**
	Ratio of Undershoots (%)	100.0	**19.8**

Table 5.10 Ratio (%) of Overshoots and undershoots out of the Specified Comfort Range: PMV, Basecase

System Operation	Magnitude of Shoots	PMV Control w/o ANN	PMV Control with ANN
PMV Increasing (Heating and Humidifying in Winter)	Magnitude of Overshoots (PMV*minutes)	5.78	**0.00**
	Magnitude of Undershoots (PMV*minutes)	-9.11	**-0.65**
PMV Decreasing (Cooling and Dehumidifying in Summer)	Magnitude of Overshoots (PMV*minutes)	14.10	**1.65**
	Magnitude of Undershoots (PMV*minutes)	-23.51	**-8.81**

Table 5.11 Magnitude (PMV*minutes) of Overshoots and undershoots out of the Specified Comfort Range: PMV, Basecase

5.2.2.2 Architectural Variables

Features of overshoots and undershoots were parametrically analyzed for the architectural variables.

a. Orientation

Features of overshoots and undershoots using the control logic were investigated for diverse orientations.

<u>Winter</u>

The ratios of overshoots and undershoots out of the specified comfort range for air temperature were all 100.0% using the conventional logic, while those using the predictive logic were in most cases zero (Figure 5.29). The exceptional cases were 0.2% for North and South-West. Therefore, the magnitudes of shoots using the predictive logic were zero for most orientations except -0.05 and -0.07 (°C*minutes) for North and South-West, respectively (Figure 5.30). On the other hand, the magnitude of overshoots and undershoots using the conventional logic demonstrated discomfort for overshoots (from 3.72°C*minutes for South-East to 4.41°C*minutes for West) and undershoots (from -5.75°C*minutes for South-West to -7.29°C*minutes for North). These comparisons indicate that the predictive control logic would maintain air temperature more comfortably than the conventional logic for all directions.

The same occurs with the humidity. The ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0%, while those using the predictive logic were reduced in most cases to 0.0% (Figure 5.31). The exceptional cases were 100.0% of overshoots for North and South-West, and 100.0% of undershoots for North and West. The high percentage of these cases can be attributed to the low frequency of system on-off times. The number of on-off times for each case was 1; thus, 100.0% meant that 1 out of 1 over- or undershoot went out of the specified comfort range. The magnitudes of shoots was slightly reduced by the predictive logic in most cases except for the overshoots of North and South-West (Figure 5.32). In these cases, although the numbers were small, the magnitudes increased from 0.07 to 0.39 (%*minutes) and from 0.01 to 0.11 (%*minutes), respectively. This increase seemed to be due to the insignificant time lag for humidity control. Therefore, it can be concluded that while the ANN-based predictive control logic would be generally advantageous for reducing overshoots and undershoots for humidity, it cannot be guaranteed for all cases.

For PMV, compared to the ratios using a logic without ANN which were all 100.0%, the ratios using a predictive logic were significantly improved to 0.0 ~ 17.6% (Figure 5.33). Magnitudes of shoots were also reduced using the predictive logic (Figure 5.34). While the values were from 5.37 (South-East) to 6.34 (South-West) (PMV*minutes) for overshoots and from -9.11 (South) to -11.33 (North-East) (PMV*minutes) for undershoots using PMV control without ANN, those using the predictive logic were from 0.0 to 1.18 (North-East) (PMV*minutes) for overshoots and from 0.0 to -5.38 (North-West) (PMV*minutes) for undershoots. As a result, PMV was also better controlled using the logic with the ANN model for all directions.

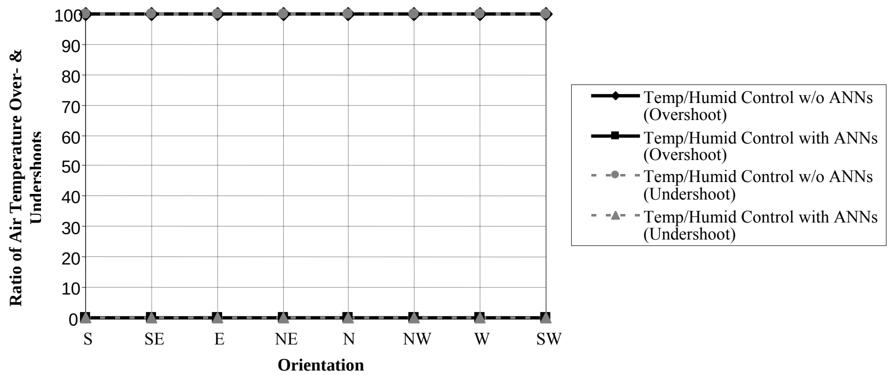

Figure 5.29 Comparison of the Ratio of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Heating: Orientation

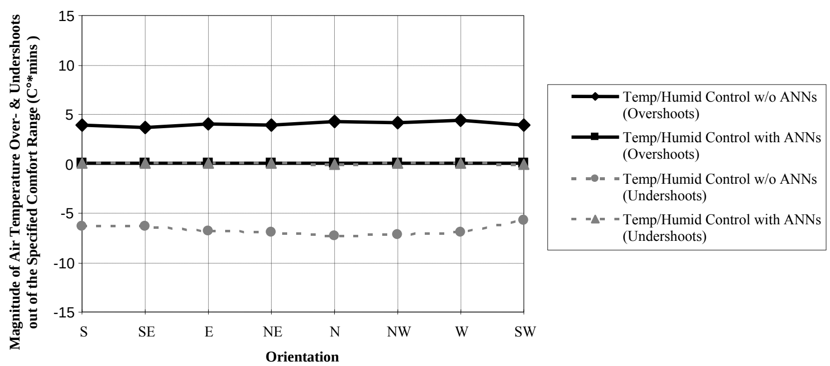

Figure 5.30 Comparison of the Magnitude of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Heating: Orientation

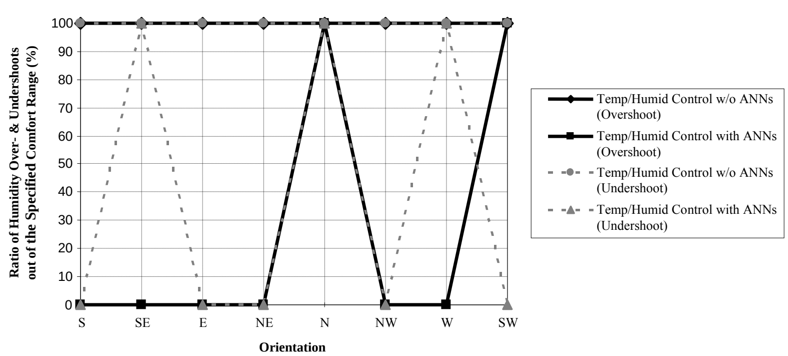

Figure 5.31 Comparison of the Ratio of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Humidifying: Orientation

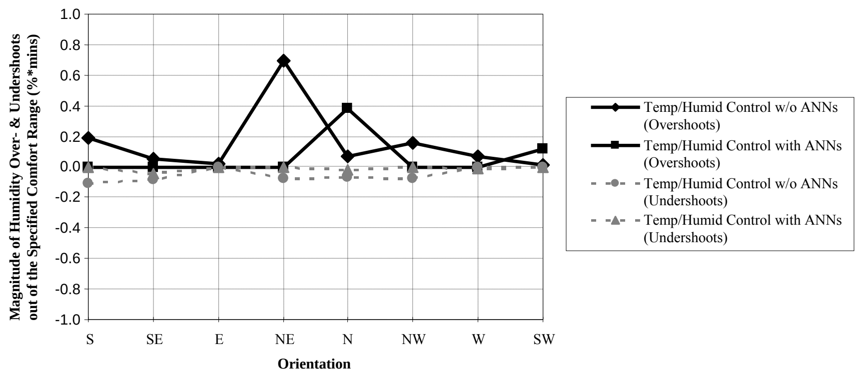

Figure 5.32 Comparison of the Magnitude of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Humidifying: Orientation

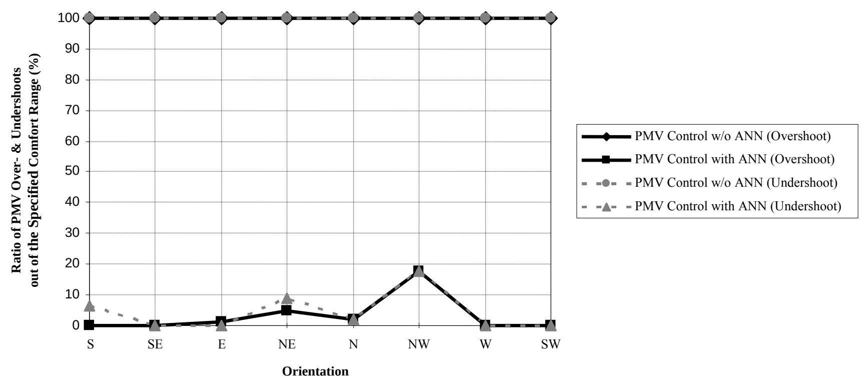

Figure 5.33 Comparison of the Ratio of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Increasing (Heating and Humidifying): Orientation

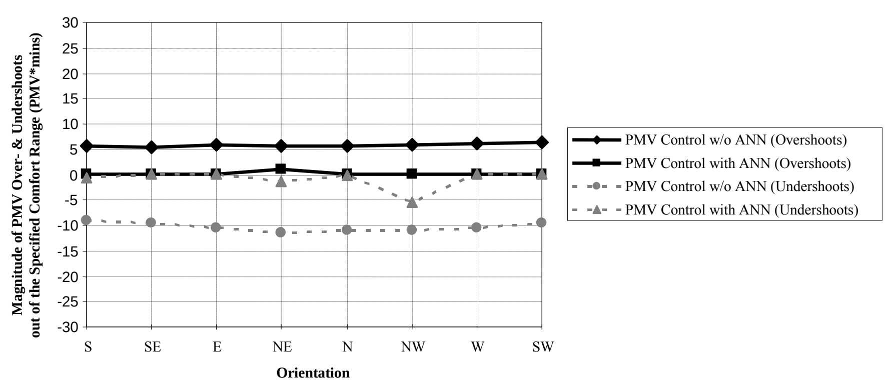

Figure 5.34 Comparison of the Magnitude of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Increasing (Heating and Humidifying): Orientation

Summer

The ratios of overshoots and undershoots for air temperature were all 100.0% using the conventional logic, while those using the predictive logic were in most cases zero (Figure 5.35) except for 0.4% for North-West. In addition, the magnitudes of shoots using the predictive logic were zero except for 1.09°C*minutes for North-West (Figure 5.36). On the other hand, the magnitudes of shoots using the conventional logic demonstrated discomfort for overshoots (from 3.62°C*minutes for North-East to 5.35°C*minutes for South) and for undershoots (from -6.59°C*minutes for South to -9.11°C*minutes for North-West). Based on these results, the predictive control logic can be seen to maintain air temperature more comfortably than the conventional logic for all directions.

The ratios of overshoots and undershoots for humidity using the conventional logic were reduced by the predictive logic (Figure 5.37). The values for the ratios went from 0.0 to 30.0% (North) for humidifying and from 0.0 to 30.0% (South-West) for dehumidifying. In most cases, magnitudes of shoots were also reduced using the predictive logic except for undershoots of North-East, North-West, West, and South-West (Figure 5.38). In these cases, magnitudes increased slightly from -0.63 to -1.45, from -0.46 to -1.23, from -0.99 to -3.45, from -0.46 to -3.21 %*minutes, respectively. From these comparisons, it can be concluded that the predictive control with the ANN model would be generally advantageous for reducing overshoots and undershoots for humidity, but can not be guaranteed for all cases.

Compared to the ratios using the logic without ANN, which were all 100.0%, the ratios using the predictive logic significantly improved to between 0.1 (overshoots of East and West) and 26.4% (undershoots of North-West) (Figure 5.39). Magnitudes of shoots were also reduced by the PMV control with ANN (Figure 5.40). While the values were from 8.43 (North-East) to 14.09 (South) PMV*minutes for overshoots and from -23.51 (South) to -27.40 (North-West) PMV*minutes for undershoots using PMV control without ANN, those using PMV control with ANN were from 0.002 (East) to 1.65 (South) PMV*minutes for overshoots and from -0.36 (South-East) to –17.72 (North-

West) PMV*minutes for undershoots. Based on these results, it can be determined that the ANN-based predictive PMV control logic controlled PMV better for all directions.

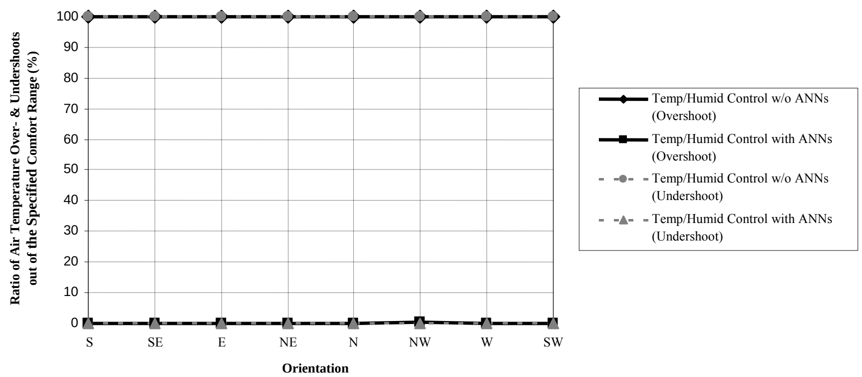

Figure 5.35 Comparison of the Ratio of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Cooling: Orientation

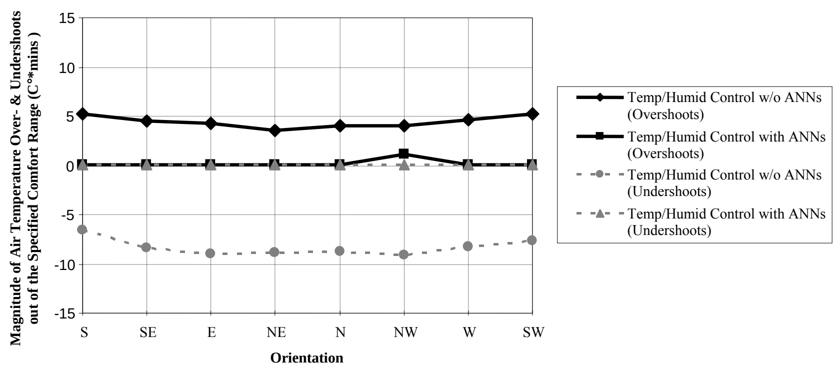

Figure 5.36 Comparison of the Magnitude of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Cooling: Orientation

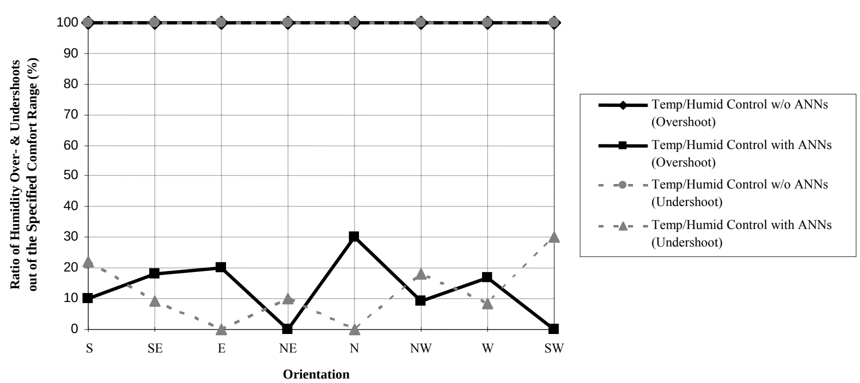

Figure 5.37 Comparison of the Ratio of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Dehumidifying: Orientation

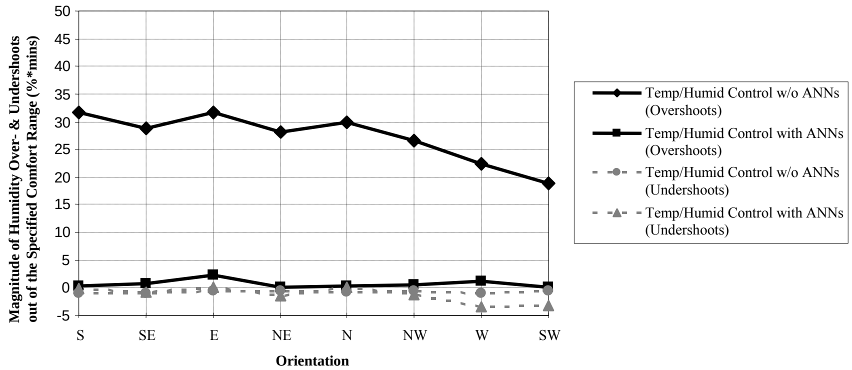

Figure 5.38 Comparison of the Magnitude of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Dehumidifying: Orientation

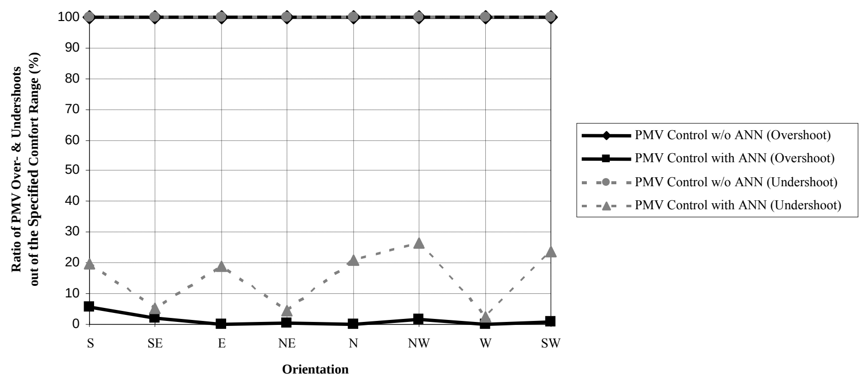

Figure 5.39 Comparison of the Ratio of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Decreasing (Cooling and Dehumidifying): Orientation

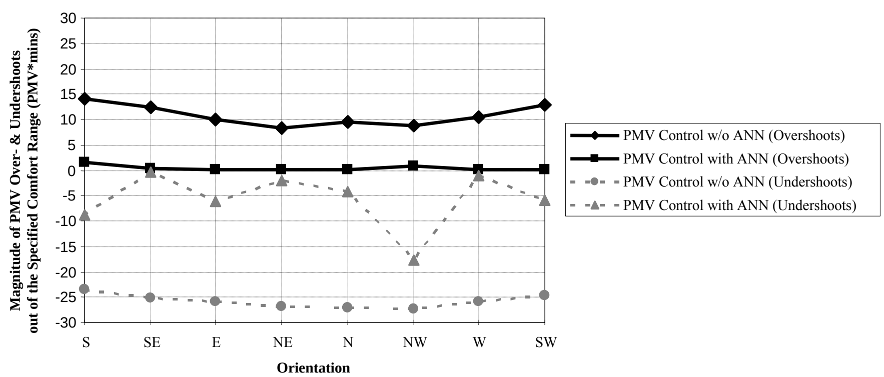

Figure 5.40 Comparison of the Magnitude of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Decreasing (Cooling and Dehumidifying): Orientation

b. R-values for Walls

Features of overshoots and undershoots using control logic were parametrically investigated for R-values for walls.

Winter

Compared to the ratios of overshoots and undershoots for air temperature using the conventional logic, which were all 100.0%, those using the predictive logic were zero in most cases (Figure 5.41). The ratios in a couple of cases were close to zero: 0.1% (undershoot of R50) to 0.5% (overshoots of R40). The conventional logic showed the uncomfortable air temperature conditions through the magnitudes of shoots, which were from 3.42°C*minutes for R10 to 4.80°C*minutes for R30 for overshoots and from -4.10°C*minutes for R10 to -6.10°C*minutes for R19 and 30 for undershoots. Compared to the conventional logic, the magnitudes of the predictive logic significantly decreased, such that they were 0.0 in most cases, and up to 0.60°C*minutes for overshoot for R40 (Figure 5.42). These results indicate that the predictive logic conditions the air temperature better within the specified comfort range for diverse wall insulation levels.

As of air temperature, the ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0%, while those using the predictive logic were reduced to between 0.0% and 33.3%, with the exception of the overshoot in R15 (Figure 5.43). The ratio of R15 walls was 100.0%, likely due to the low frequency of system on-off times (2 out of 2 overshoots). There were no over- and undershoots from R30 to 50 since no humidifying operation occurred. Magnitudes of shoots were slightly reduced by the predictive logic in most cases except for the overshoots of R15 (Figure 5.44). In this case, even though the numbers were small, magnitude increased from 0.07 to 0.58 %*minutes due to the low frequency (twice for overshoot and undershoot).

Compared to the ratios of overshoots and undershoots for PMV using the PMV control without ANN, which were all 100.0%, the ratios using the PMV control with ANN improved significantly to 0.0 ~ 10.9% (Figure 5.45). Magnitudes of shoots were also reduced using PMV control with ANN (Figure 5.46). The magnitude values using the PMV control without ANN were from 3.87 (R10) to 6.82 (R40) PMV*minutes for overshoots and from -5.39 (R10) to -8.28 (R50) PMV*minutes for undershoots. In contrast, those using PMV control with ANN were 0.00 PMV*minutes for overshoots for all R-values except for 0.04 (R15) PMV*minutes and from 0.00 to -2.84 (R50) PMV*minutes for undershoots. As a result, PMV control with ANN can be seen to control PMV more properly for diverse R-values for walls.

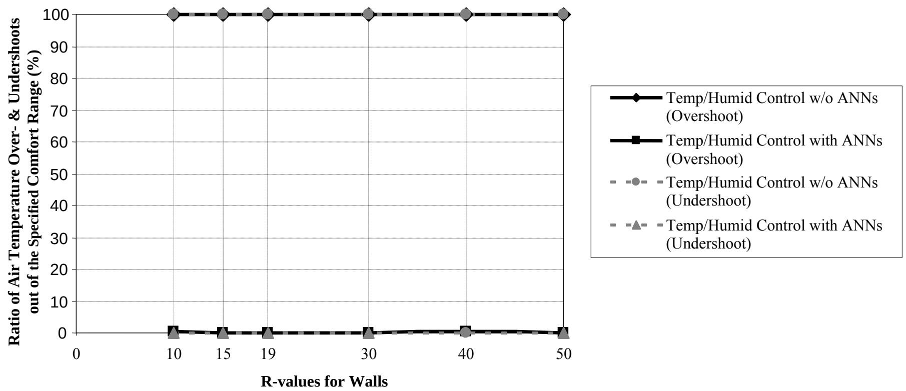

Figure 5.41 Comparison of the Ratio of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Heating: R-values for Walls

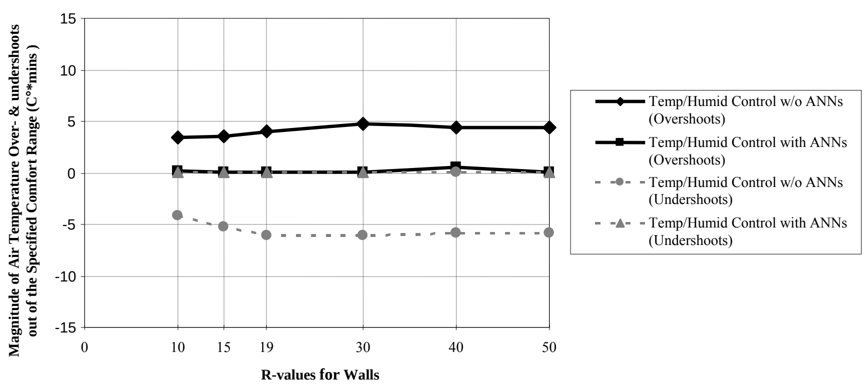

Figure 5.42 Comparison of the Magnitude of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Heating: R-values for Walls

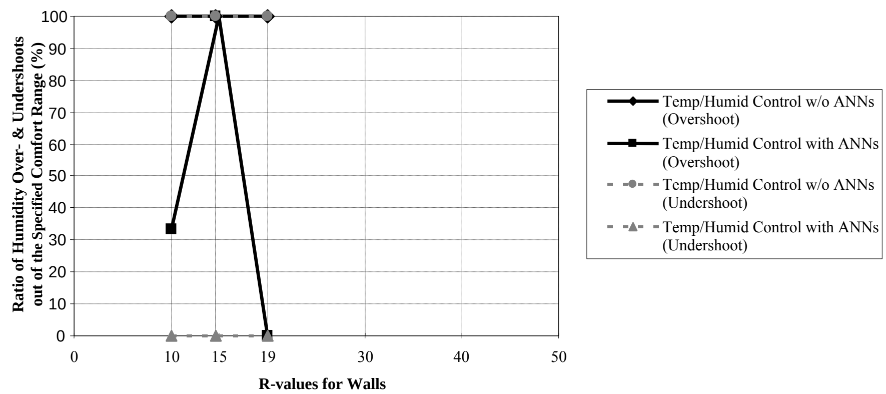

Figure 5.43 Comparison of the Ratio of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Humidifying: R-values for Walls

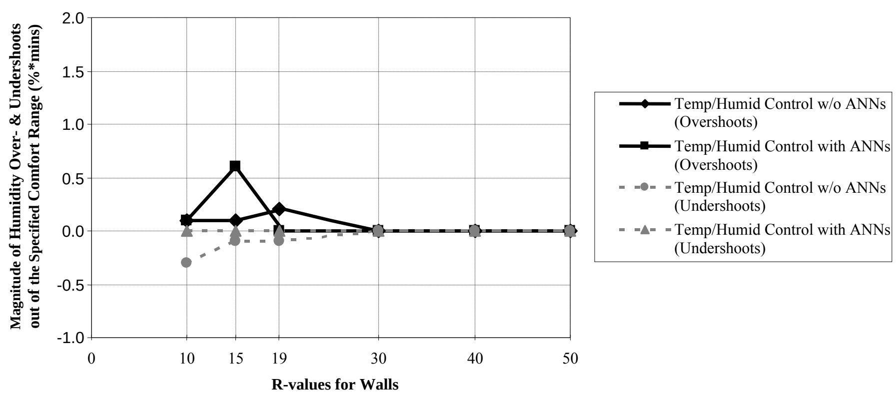

Figure 5.44 Comparison of the Magnitude of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Humidifying: R-values for Walls

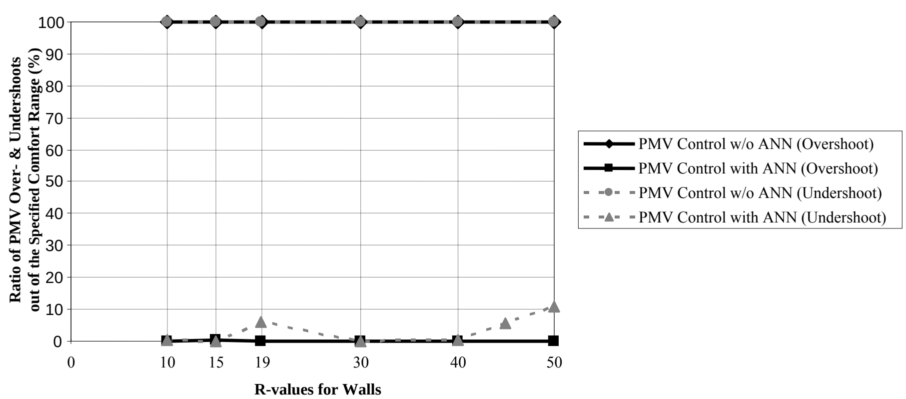

Figure 5.45 Comparison of the Ratio of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Increasing (Heating and Humidifying): R-values for Walls

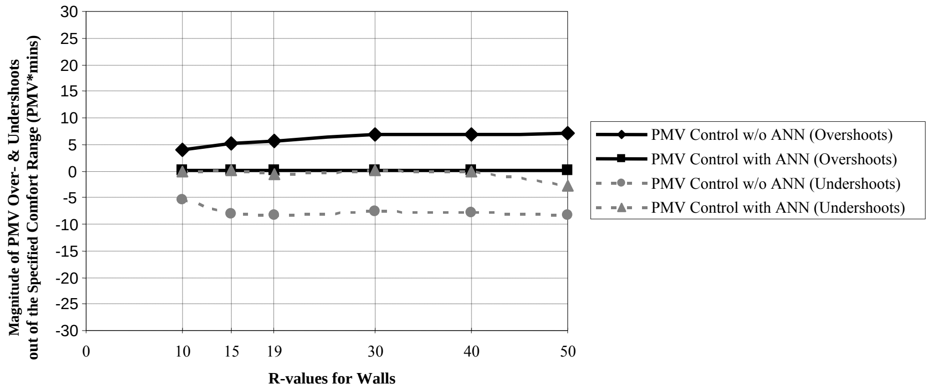

Figure 5.46 Comparison of the Magnitude of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Increasing (Heating and Humidifying): R-values for Walls

<u>Summer</u>

Compared to the ratios of overshoots and undershoots for air temperature (all 100.0%) using the conventional logic, those using the predictive logic in most cases were zero except for 0.5% for undershoots in R10 (Figure 5.47). Magnitudes using the predictive logic as well were all zero for R-values for walls, except for -1.88°C*minutes for undershoots in R10 (Figure 5.48). Those using the conventional logic were from 4.67°C*minutes for R10 to 5.75°C*minutes for R40 for overshoots and from -6.28°C*minutes for R15 to -7.36°C*minutes for R30 for undershoots. The advantages of the predictive control logic were demonstrated by these reductions in ratio and magnitude.

The same occur with the air temperature: the ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0%, while those using predictive logic were reduced to between 0.0% and 60.0% in R30 (Figure 5.49). In most cases, magnitudes of shoots were reduced using the predictive logic, with the exception of the undershoots of R15 and 30 (Figure 5.50). In these cases, magnitudes increased from -1.05 to -2.83 and from -0.91 to -2.51%*minutes, respectively. Therefore, the predictive logic can be determined to be generally advantageous for reducing overshoots and undershoots for humidity, but can not be guaranteed for all cases due to the low frequency.

Compared to the ratios of overshoots and undershoots for PMV using the PMV control without ANN which were all 100.0%, the ratios using the PMV control with ANN improved significantly to between 4.2% (undershoot of R19 and 30) and 30.4%

(overshoot of R15) (Figure 5.51). Magnitude values using the PMV control without ANN were from 11.87 (R50) to 15.92 (R10) PMV*minutes for overshoots and from -19.55 (R10) to -26.80 (R40) PMV*minutes for undershoots (Figure 5.52). In contrast, those using PMV control with ANN were reduced to between 1.65 (R19) and 14.35 (R15) PMV*minutes for overshoots for all R-values and between -0.33 (R10) and -8.96 (R50) PMV*minutes for undershoots. From these comparisons, it is clear that PMV control with ANN reduced overshoots and undershoots for PMV for R-values for walls.

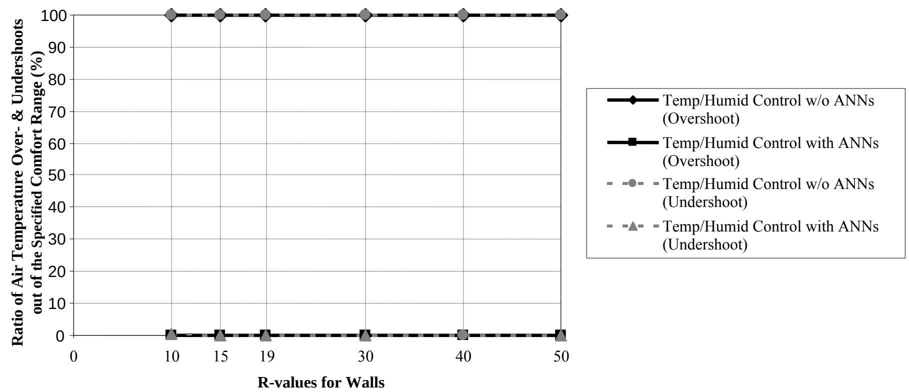

Figure 5.47 Comparison of the Ratio of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Cooling: R-values for Walls

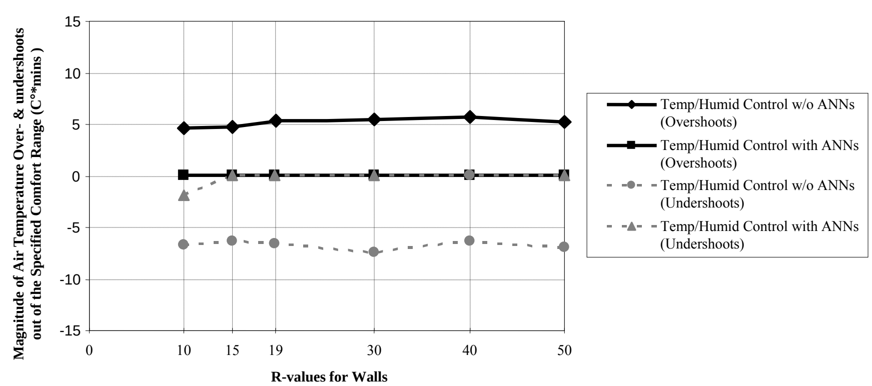

Figure 5.48 Comparison of the Magnitude of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Cooling: R-values for Walls

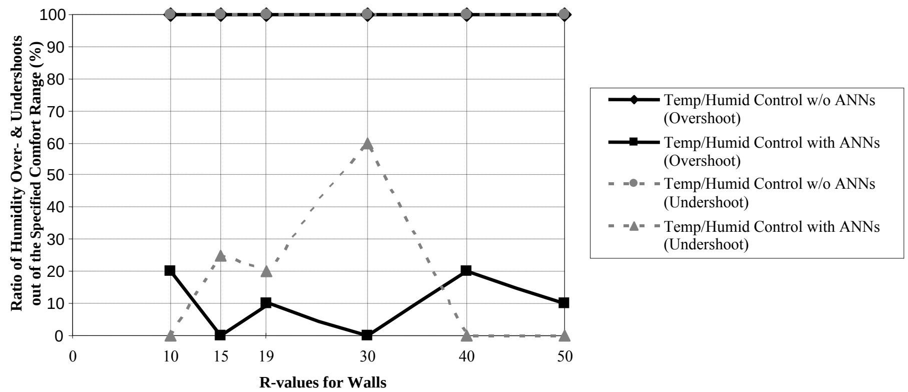

Figure 5.49 Comparison of the Ratio of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Dehumidifying: R-values for Walls

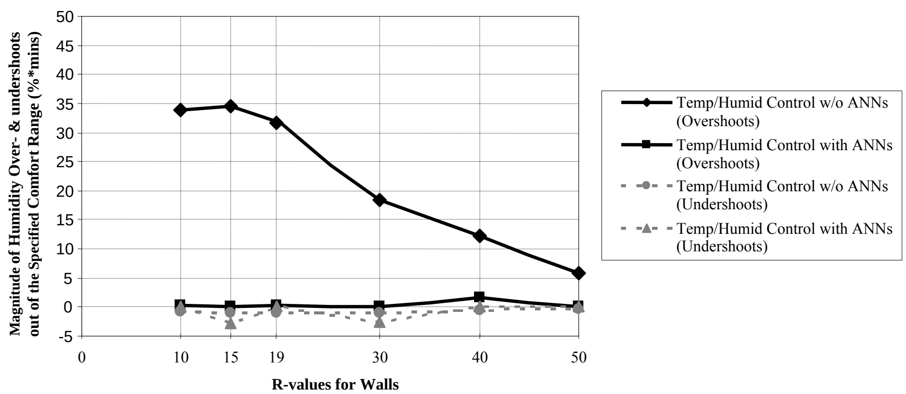

Figure 5.50 Comparison of the Magnitude of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Dehumidifying: R-values for Walls

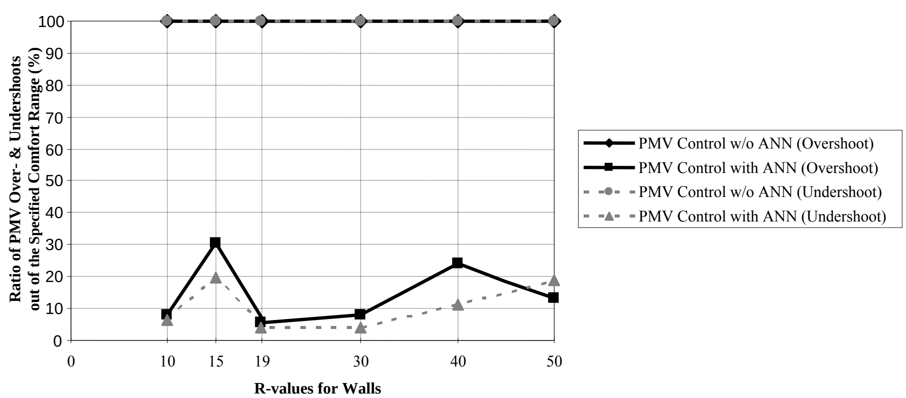

Figure 5.51 Comparison of the Ratio of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Decreasing (Cooling and Dehumidifying): R-values for Walls

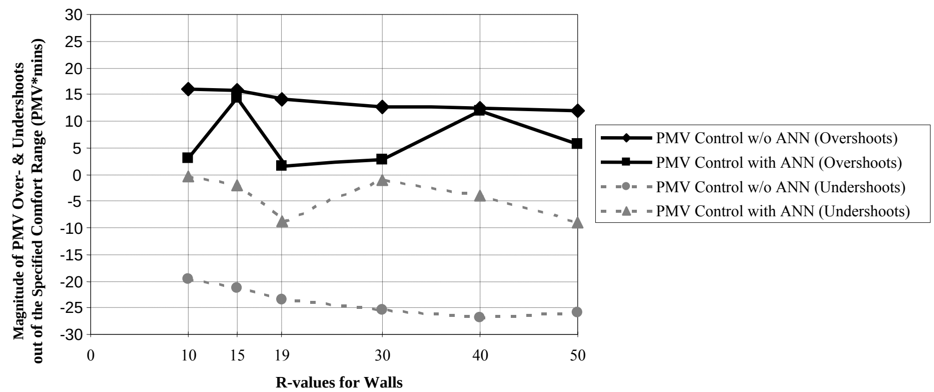

Figure 5 52 Comparison of the Magnitude of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Decreasing (Cooling and Dehumidifying): R-values for Walls

c. R-values for the Roof

The ratios and magnitudes of overshoots and undershoots out of the specified comfort range were parametrically investigated for R-values of the roof.

Winter

The ratios of overshoots and undershoots for air temperature were all 100.0% using the conventional logic while those using the predictive logic were in most cases zero, with the exception of 0.2% (R40) and 1.4% (R10) for overshoots and 0.2% (R40) for undershoots (Figure 5.53). Magnitudes using the predictive logic as well were all zero for R-values of the roof except for 0.20°C*minutes (R40) and 0.49°C*minutes (R10) for overshoots and -0.45°C*minutes (R40) for undershoots (Figure 5.54). Those using the conventional logic were larger: from 3.42°C*minutes for R10 to 4.17°C*minutes for R80 for overshoots and from -5.10°C*minutes for R10 to -6.10°C*minutes for R38 for undershoots. As the comparison clearly indicates, the features of overshoots and undershoots were improved by the predictive control logic.

The ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0%, while those using the predictive logic were reduced to 0.0% in all cases except for 50.0% in R20 (1 out of 2 overshoots and 1 out of 2 undershoots) (Figure 5.55). In all cases, magnitudes of shoots were reduced by the predictive logic (Figure

5.56). Compared to the magnitudes, between 0.002%*minutes (R60) and 0.90%*minutes (R10) for overshoots and between -0.001%*minutes (R50) and -0.14%*minutes (R60) for undershoots using the conventional logic, those using the predictive logic were all zero except for 0.07%*minutes for overshoots and 0.01%*minutes for undershoots (R20). These comparisons demonstrate that the predictive logic can improve the features of overshoots and undershoots for humidity.

Compared to the ratios of overshoots and undershoots for PMV using the PMV control without ANN, which were all 100.0%, the ratios using the PMV control with ANN improved significantly to between 0.0% for most cases and 6.0% for undershoot of R38 (Figure 5.57). Magnitudes were reduced for all R-values (Figure 5.58). Magnitude values using the PMV control without ANN were from 4.46 PMV*minutes (R10) to 6.21 PMV*minutes (R80) for overshoots and from -6.14 PMV*minutes (R10) to -9.09 PMV*minutes (R30) for undershoots. In contrast, those using PMV control with ANN were reduced to 0.0 PMV*minutes for overshoots for all R-values and between 0.00 PMV*minutes in most cases and -0.65 PMV*minutes (R38) for undershoots. Based on these comparisons, PMV control with ANN has shown its potential for reducing overshoots and undershoots for PMV.

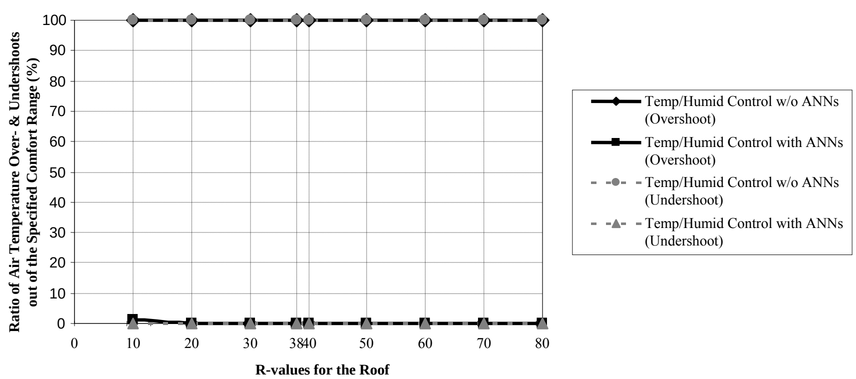

Figure 5.53 Comparison of the Ratio of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Heating: R-values for the Roof

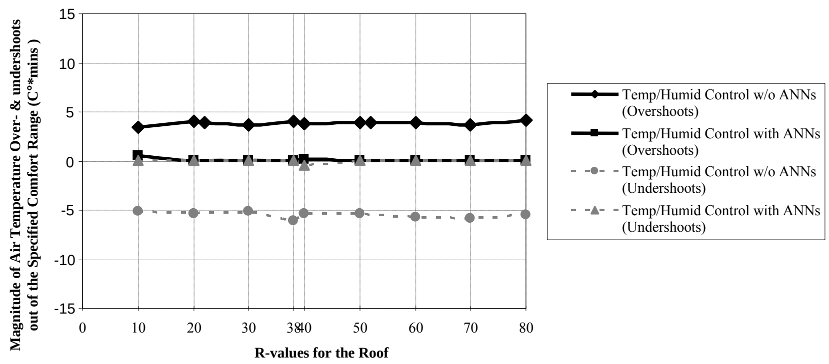

Figure 5.54 Comparison of the Magnitude of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Heating: R-values for the Roof

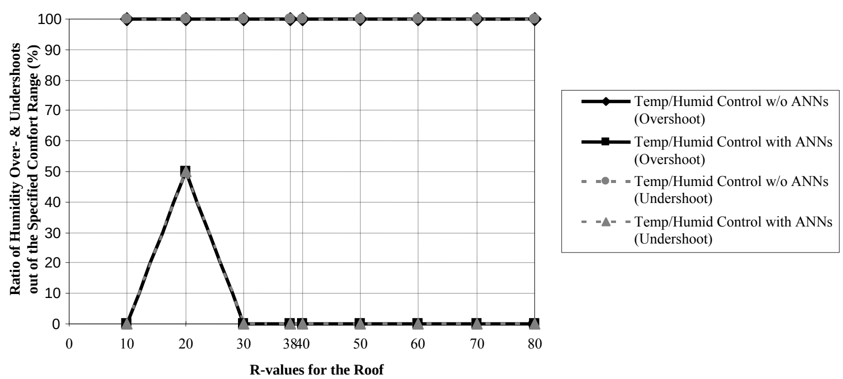

Figure 5.55 Comparison of the Ratio of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Humidifying: R-values for the Roof

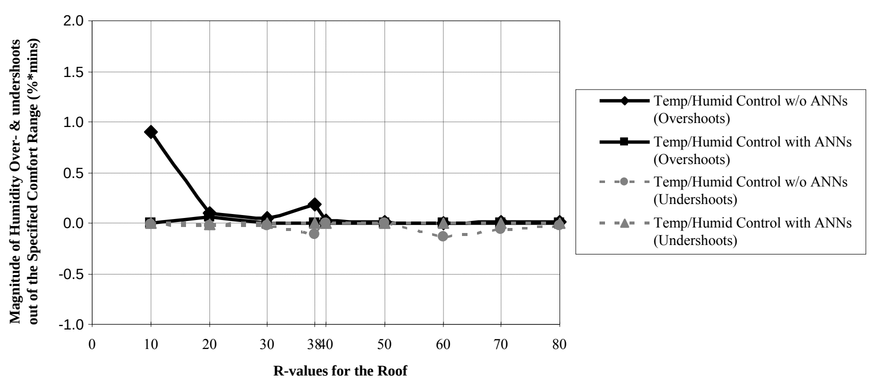

Figure 5.56 Comparison of the Magnitude of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Humidifying: R-values for the Roof

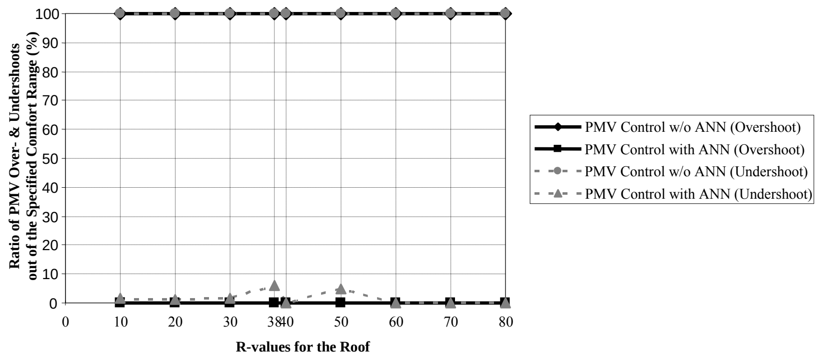

Figure 5.57 Comparison of the Ratio of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Increasing (Heating and Humidifying): R-values for the Roof

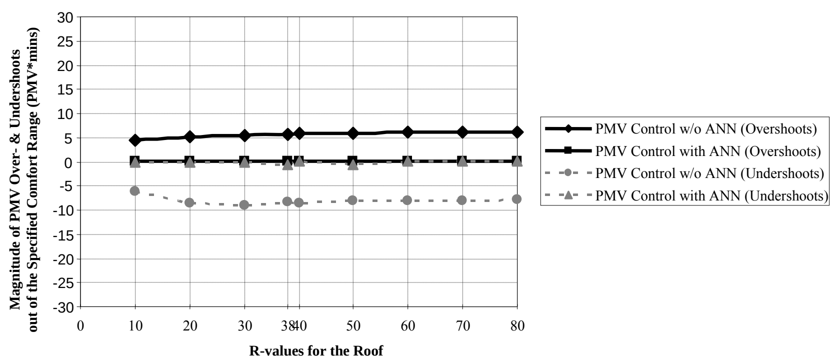

Figure 5.58 Comparison of the Magnitude of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Increasing (Heating and Humidifying): R-values for the Roof

<u>Summer</u>

Compared to the ratios of overshoots and undershoots for air temperature using the conventional logic, which were all 100.0%, those using the predictive logic were zero in most cases except for 0.2% (R40) for overshoots and 0.4% (R40) for undershoots (Figure 5.59). Magnitudes using the predictive logic were also all zero for R-values of the roof, with the exception of 0.16°C*minutes (R40) for overshoots and -0.65°C*minutes (R40) for undershoots (Figure 5.60). Those using the conventional logic were from 4.61°C*minutes for R60 to 5.41°C*minutes for R38 for overshoots and from -6.79°C*minutes for R70 to -7.66°C*minutes for R10 for undershoots. Based on this comparison, the predictive control logic can be seen to improve the features of overshoots and undershoots for diverse R-values of the roof.

The ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0%, while those using the predictive logic were reduced to between 0.0% and 40.0% in R40 (4 out of 10 overshoots) (Figure 5.61). Magnitudes of shoots were reduced using the predictive logic in all cases (Figure 5.62). Compared to the magnitudes using the conventional logic, between 13.71%*minutes (R80) and 37.93%*minutes (R20) for overshoots and between -0.40%*minutes (R20) and -1.45%*minutes (R40) for undershoots, those using the predictive logic were reduced to between zero to 0.93%*minutes for overshoots (R20) and to -0.89%*minutes for undershoots (R40). Therefore, the predictive logic demonstrates the improvement in the stability of humidity for diverse levels of the roof insulation.

Compared to the ratios of overshoots and undershoots for PMV using the PMV control without ANN, which were all 100.0%, those using the PMV control with ANN improved significantly to between 0.0% for overshoots for R70 and 27.0% for undershoots of R70 (Figure 5.63). Magnitudes were also reduced for all R-values (Figure 5.64). Compared to the magnitude values using the PMV control without ANN, which were between 14.01 PMV*minutes (R70) and 15.63 PMV*minutes (R20) for overshoots and between -18.62 PMV*minutes (R10) and -23.51 PMV*minutes (R38) for undershoots, those using PMV control with ANN ranges between 0.00 PMV*minutes (R70) and 7.59 PMV*minutes (R80) for overshoots and between -2.47 PMV*minutes (R20) and -13.27 PMV*minutes (R70) for undershoots. These comparisons indicate that the predictive PMV control with the ANN model would control PMV better within the specified comfort range than the PMV control without the ANN model.

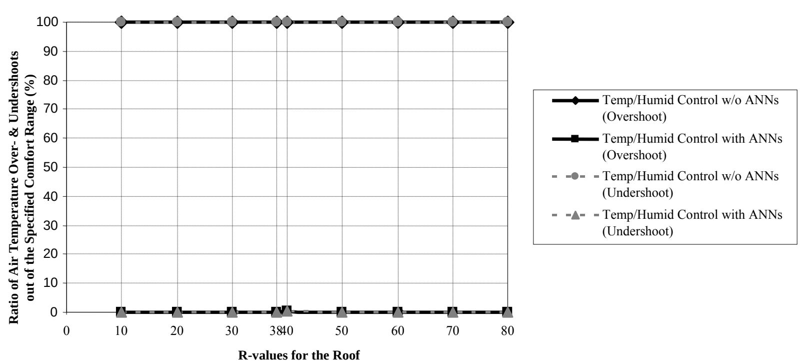

Figure 5.59 Comparison of the Ratio of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Cooling: R-values for the Roof

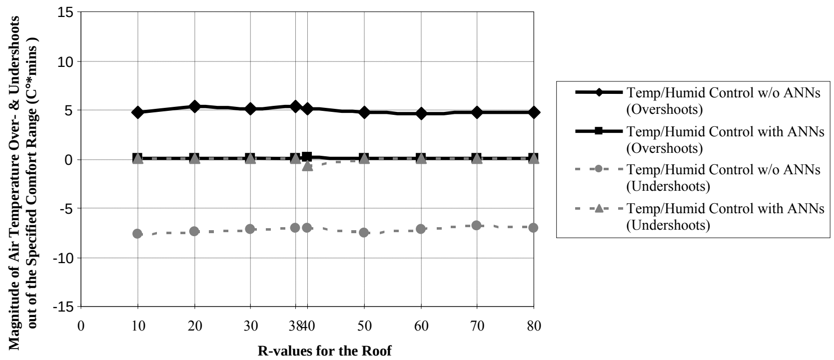

Figure 5.60 Comparison of the Magnitude of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Cooling: R-values for the Roof

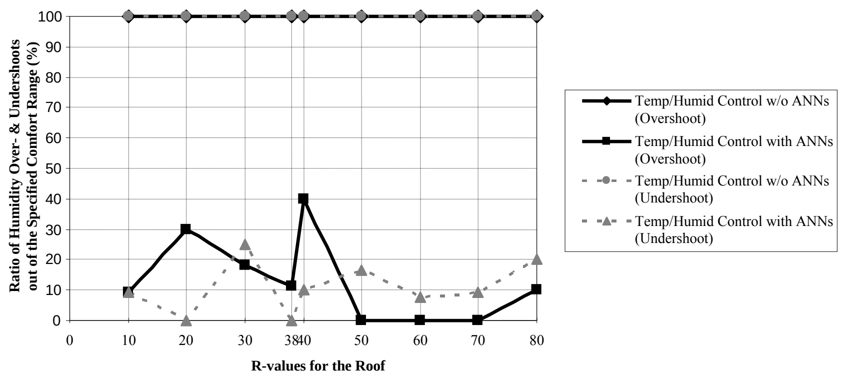

Figure 5.61 Comparison of the Ratio of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Dehumidifying: R-values for the Roof

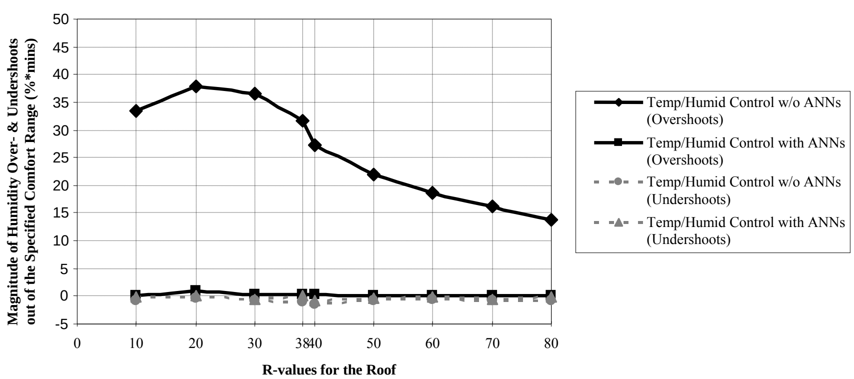

Figure 5.62 Comparison of the Magnitude of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Dehumidifying: R-values for the Roof

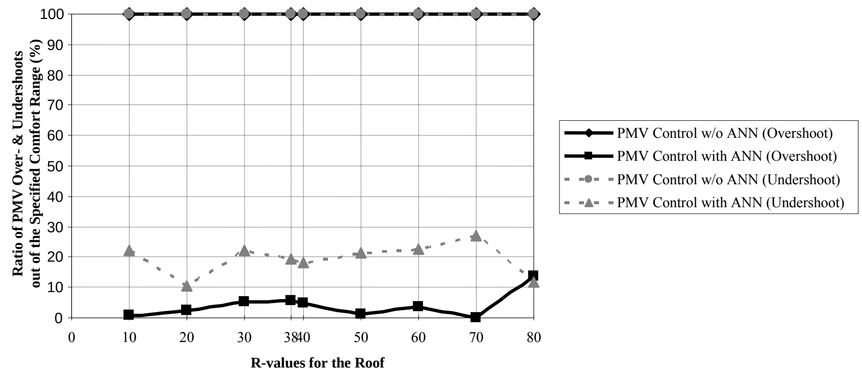

Figure 5.63 Comparison of the Ratio of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Decreasing (Cooling and Dehumidifying): R-values for the Roof

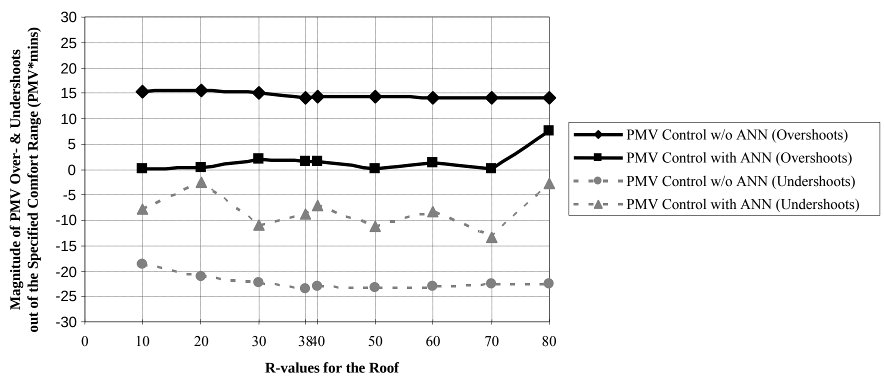

Figure 5.64 Comparison of the Magnitude of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Decreasing (Cooling and Dehumidifying): R-values for the Roof

d. R-values for Windows

The ratios and magnitudes of overshoots and undershoots out of the specified comfort range were parametrically investigated for R-values for windows.

Winter

The ratios of overshoots and undershoots for air temperature were all 100.0% using the conventional logic, while those using the predictive logic were zero in most cases except for 0.2% (R5) for overshoots (Figure 5.65). Magnitudes using the predictive logic were all reduced to zero for R-values of the roof except for 0.03°C*minutes (R5) for overshoots (Figure 5.66). Those using the conventional logic were from

1.84°C*minutes for R1 to 3.89°C*minutes for R4 for overshoots and from -3.20°C*minutes for R9 to -4.89°C*minutes for R3.44 for undershoots. These results demonstrate that the overshoots and undershoots for air temperature for R-values for windows were reduced using the predictive control logic.

The ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0%, while those using the predictive logic were reduced to 0.0% in many cases except for 100.0% for overshoots in R5, 6, 8, 9, and 10 (1 out of 1 for R8 and 2 out of 2 for R5, 6, 9, and 10) and for undershoots in R3 and 8 (1 out of 1 for both) (Figure 5.67). Magnitudes of shoots were reduced using the predictive logic in most cases (Figure 5.68). It increased, however, using the predictive logic in cases such as from 0.01 to 0.06%*minutes (R6), from 0.05 to 0.08%*minutes (R8), and from 0.03 to 0.08%*minutes (R10) for overshoots and from -0.01 to -0.06%*minutes (R8) for undershoots. Based on these comparisons, the predictive logic generally demonstrates the improved features of overshoots and undershoots for humidity, but is not guaranteed for all cases.

Compared to the ratios of overshoots and undershoots for PMV using the PMV control without ANN, which were all 100.0%, the ratios using the PMV control with ANN improved significantly to between 0.0% for most cases and 6.7% for undershoots of R4 (Figure 5.69). Magnitudes were reduced for all R-values (Figure 5.70). Magnitude values using the PMV control without ANN were from 2.39 (R1) to 7.04 PMV*minutes (R10) for overshoots and from -4.92 (R1) to -7.40 PMV*minutes (R3) for undershoots. In contrast, those using PMV control with ANN were between 0.0 PMV*minutes in most cases to -1.67 PMV*minutes (R4) for undershoots. It can thus be concluded that the PMV control with ANN can significantly reduce the overshoots and undershoots for PMV.

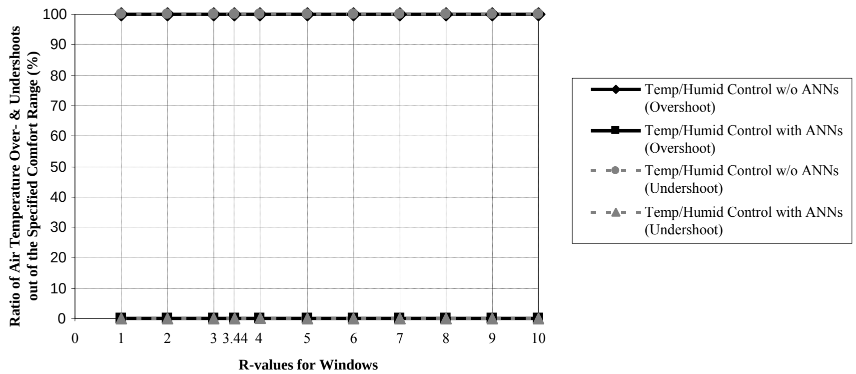

Figure 5.65 Comparison of the Ratio of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Heating: R-values for Windows

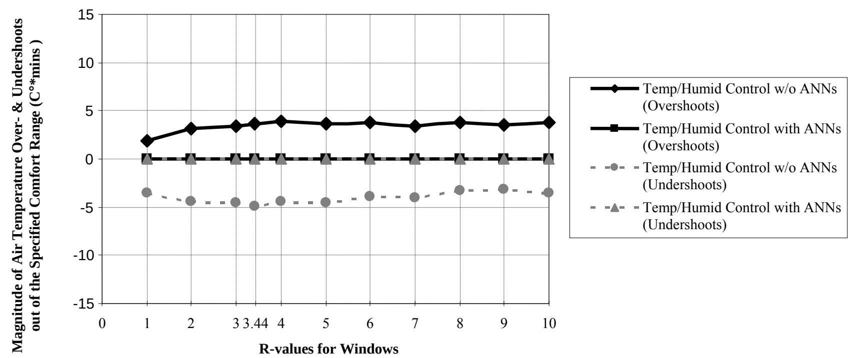

Figure 5.66 Comparison of the Magnitude of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Heating: R-values for Windows

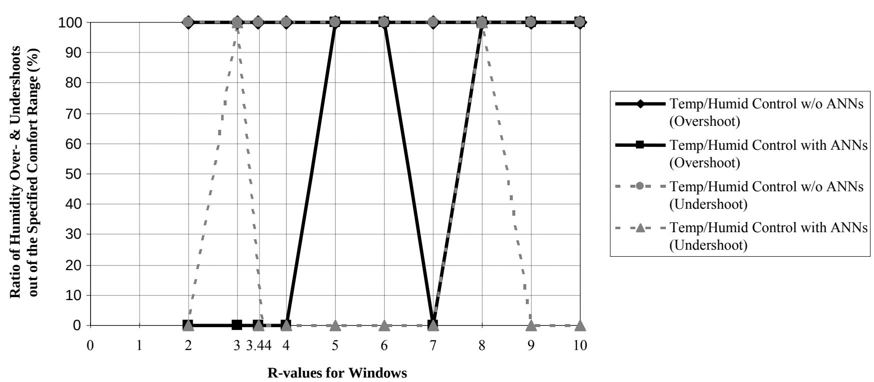

Figure 5.67 Comparison of the Ratio of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Humidifying: R-values for Windows

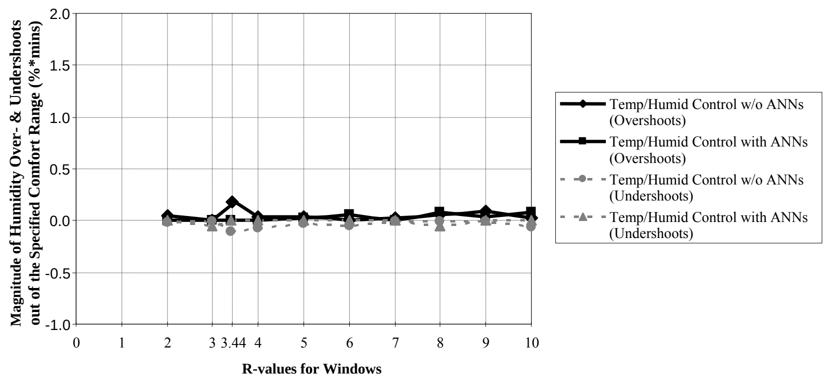

Figure 5.68 Comparison of the Magnitude of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Humidifying: R-values for Windows

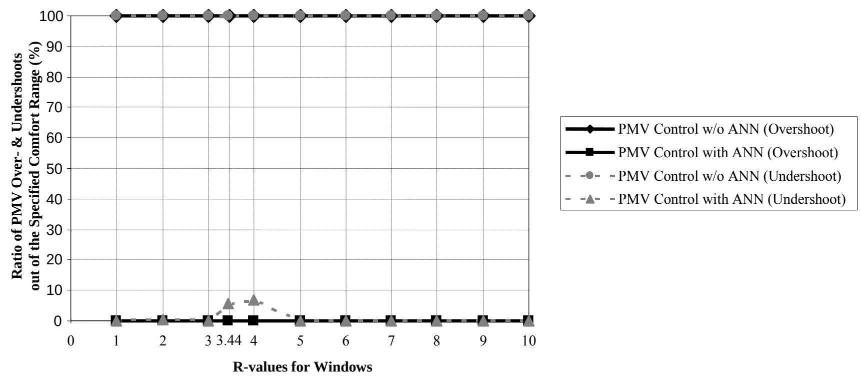

Figure 5.69 Comparison of the Ratio of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Increasing (Heating and Humidifying): R-values for Windows

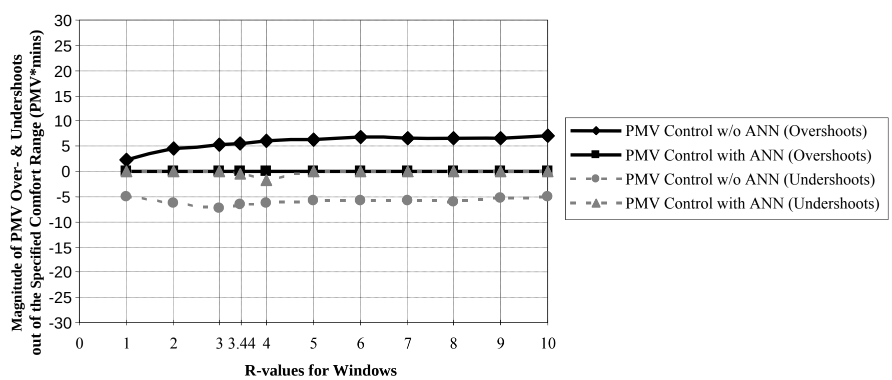

Figure 5.70 Comparison of the Magnitude of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Increasing (Heating and Humidifying): R-values for Windows

Summer

Compared to the ratios of overshoots and undershoots for air temperature (all 100.0%) using the conventional logic, those using the predictive logic were zero in most cases except for 0.2% (R7) and 0.4% (R5) for undershoots (Figure 5.71). Thus, magnitudes using the predictive logic were all zero for R-values for windows with the exception of -0.14°C*minutes (R5) and -0.51°C*minutes (R7) for undershoots (Figure 5.72). In contrast, those using the conventional logic were from 4.43°C*minutes for R6 to 5.38°C*minutes for R2 for overshoots and from -6.59°C*minutes for R3.44 to -7.36°C*minutes for R4 for undershoots. The advantage of the predictive control logic is thus demonstrated by these reductions in ratio and magnitude.

The same occurs with the air temperature: the ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0%, while those using the predictive logic were reduced to 0.0% to 60.0% in R8 (6 out of 10 overshoots) (Figure 5.73). Magnitudes of shoots were reduced by the predictive logic in every case (Figure 5.74). The magnitude values using the conventional logic were between 19.46 (R7) to 33.71 (R2)%*minutes for overshoots and between -0.61 (R3) to -1.47 (R2)%*minutes for overshoots. On the other hand, those using the predictive logic were between 0.00 and 4.10 (R1)%*minutes for overshoots and between 0.00 and -0.69 (R4)%*minutes for undershoots. These comparisons of the ratios and magnitudes show that the predictive logic is advantageous for reducing overshoots and undershoots for humidity.

Compared to the ratios of overshoots and undershoots for PMV using the PMV control without ANN, which were all 100.0%, the ratios using the PMV control with ANN improved significantly to between 0.6% (overshoot of R9) and 21.6% (overshoot of R1) (Figure 5.75). Magnitude values using the PMV control without ANN were from 13.23 (R8) to 15.48 (R2) PMV*minutes for overshoots and from -19.61 (R1) to -24.08 (R9) PMV*minutes for undershoots. In contrast, those using PMV control with ANN were all reduced to between 0.02 (R9) and 9.30 (R1) PMV*minutes for overshoots and between -0.63 (R2) and -14.74 (R6) PMV*minutes for undershoots (Figure 5.76). From these comparisons it is clear that PMV control with ANN reduces overshoots and undershoots of PMV for R-values for windows.

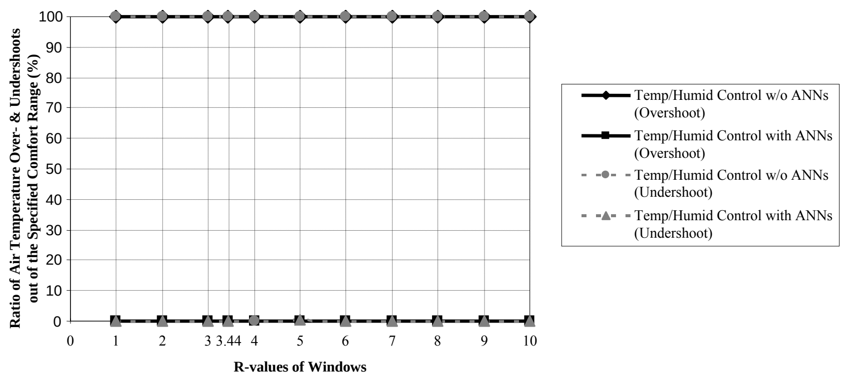

Figure 5.71 Comparison of the Ratio of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Cooling: R-values for Windows

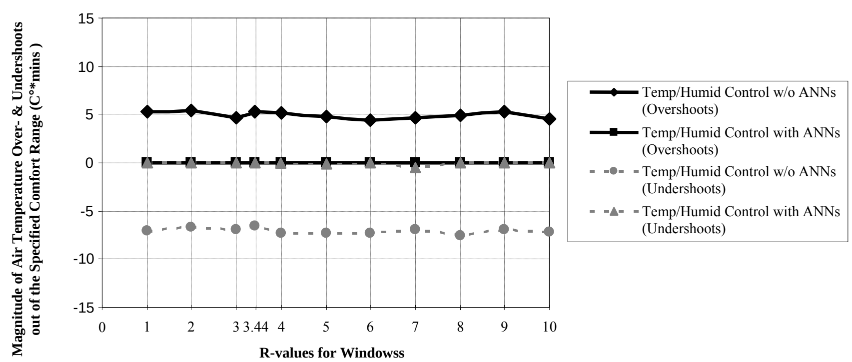

Figure 5.72 Comparison of the Magnitude of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Cooling: R-values for Windows

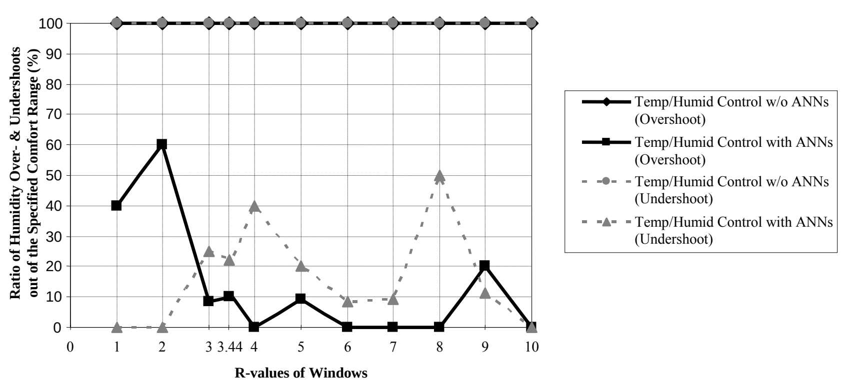

Figure 5.73 Comparison of the Ratio of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Dehumidifying: R-values for Windows

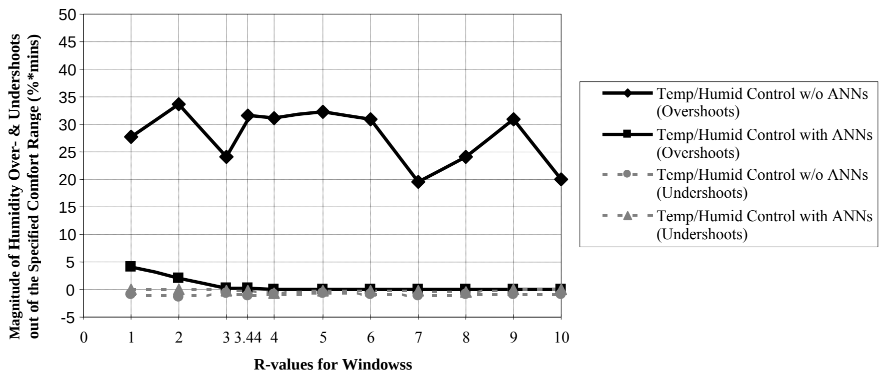

Figure 5.74 Comparison of the Magnitude of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Dehumidifying: R-values for Windows

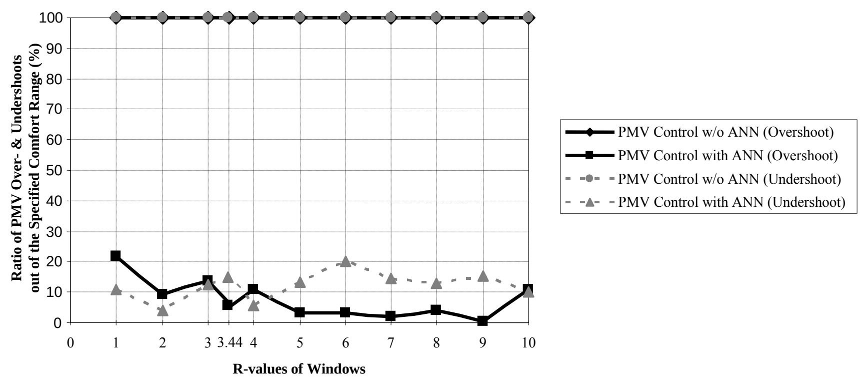

Figure 5.75 Comparison of the Ratio of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Decreasing (Cooling and Dehumidifying): R-values for Windows

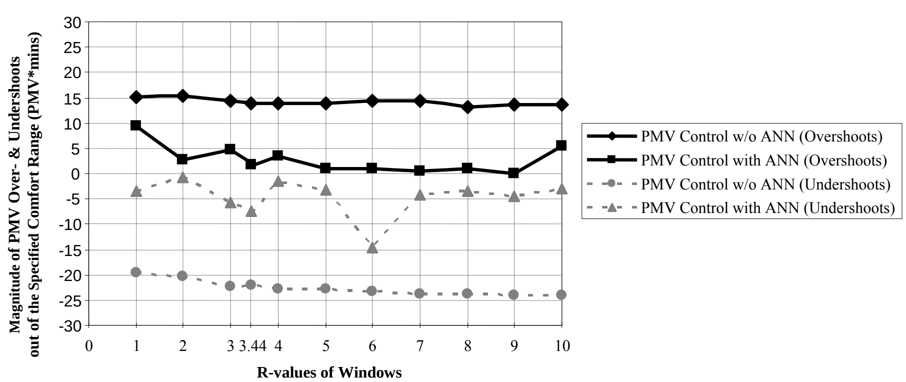

Figure 5.76 Comparison of the Magnitude of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Decreasing (Cooling and Dehumidifying): R-values for Windows

e. Window Wall Ratio

The ratios and magnitudes of overshoots and undershoots out of the specified comfort range were parametrically investigated for window wall ratio (WWR).

<u>Winter</u>

The ratios of overshoots and undershoots out of the specified comfort range for air temperature were all 100.0% using the conventional logic, while those using the predictive logic fell between zero and 1.1% in most cases for overshoots and undershoots in WWR0.4 (Figure 5.77). Magnitudes of shoots using the predictive logic were between zero in most WWR cases and maximally 0.36 (°C*minutes) for overshoots for WWR0.4 (Figure 5.78). In contrast, the magnitude of overshoots and undershoots using the conventional logic demonstrated the larger discomfort with overshoots (from 0.85°C*minutes for WWR0.45 to 4.33°C*minutes for WWR0.15) and undershoots (from -0.57°C*minutes for WWR0.4 to -2.48°C*minutes for WWR0.15). These results indicate that the predictive control logic maintains air temperature more comfortably than the conventional logic for all WWR.

The same occurs with the air temperature: the ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0%, while those using the predictive logic were reduced to 0.0% in most cases (Figure 5.79). The exceptional cases were 100.0% (1 out of 1) for overshoots for WWR0.2 and 100.0% (1 out of 1) for undershoots for WWR0.1. As no humidifying operations existed in cases over WWR0.3, overshoots and undershoots did not occur. The magnitudes of shoots were slightly reduced using the predictive logic in most cases except for the overshoot of WWR0.2 (Figure 5.80). In this case, although the numbers were small, magnitude increased from 0.001 to 0.15 (%*minutes). Therefore, the ANN-based control logic is generally advantageous for reducing overshoots and undershoots for humidity but cannot be guaranteed for all cases.

For PMV, compared to the ratios using a logic without ANN which were all 100.0%, the ratios using a logic with the ANN model improved significantly to 0.0 ~

7.4% (undershoot in WWR0.5) (Figure 5.81). In addition, magnitudes of shoots were also reduced using PMV control with ANN in most cases, with the exception of the undershoots of WWR 0.4 and 0.5 (Figure 5.82). In these cases, magnitude values increased from -1.12 to -1.32 (R0.4) and from -1.25 to -2.86 (R0.5) PMV*minutes, even though the ratio of undershoots using PMV control with ANN were significantly lower than PMV control without ANN. This increase was due to the large degree of undershoots in the early simulation period, when the training for the ANN model for large WWR was not sufficient; following training, these phenomena no longer occurred. As a result, PMV was generally controlled better using the logic with the ANN model, but not for all cases in which the magnitude of the undershoots increased. However, this undesirable situation might be improved upon with sufficient training.

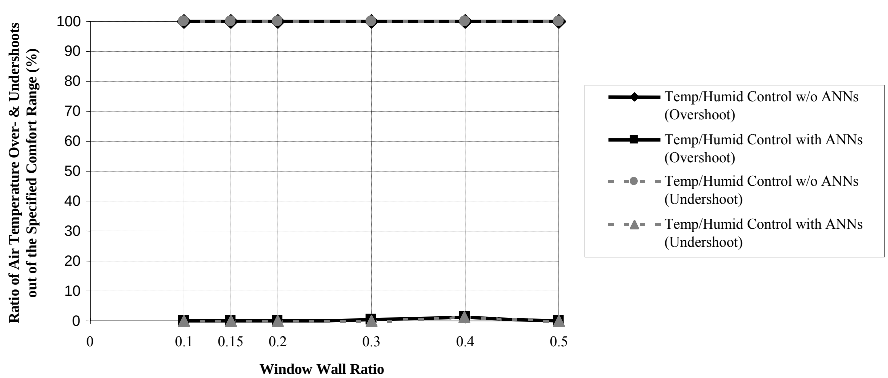

Figure 5.77 Comparison of the Ratio of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Heating: Window Wall Ratio

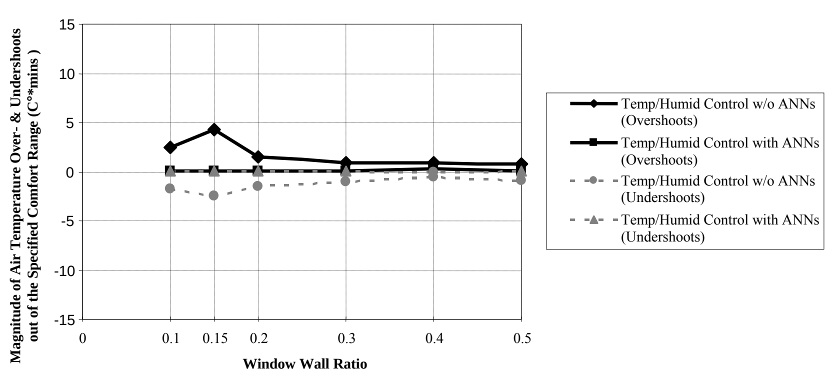

Figure 5.78 Comparison of the Magnitude of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Heating: Window Wall Ratio

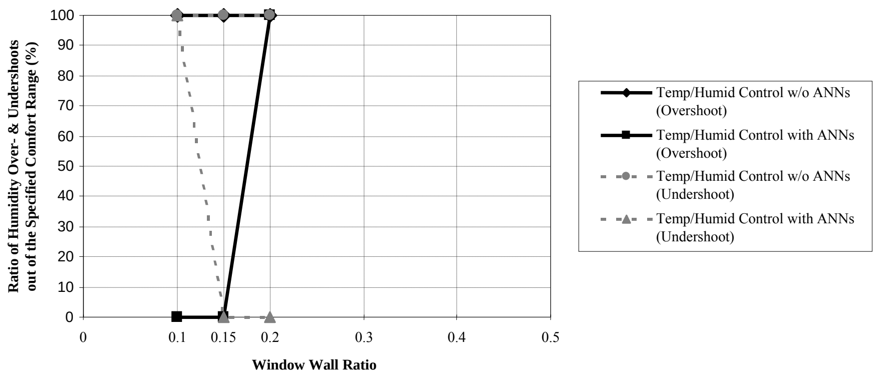

Figure 5.79 Comparison of the Ratio of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Humidifying: Window Wall Ratio

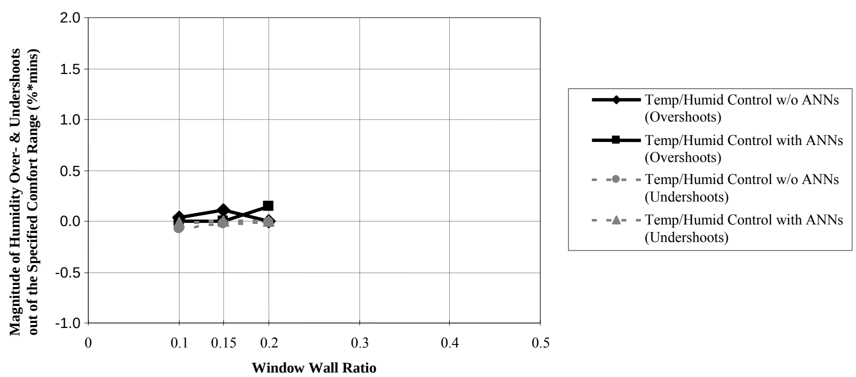

Figure 5.80 Comparison of the Magnitude of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Humidifying: Window Wall Ratio

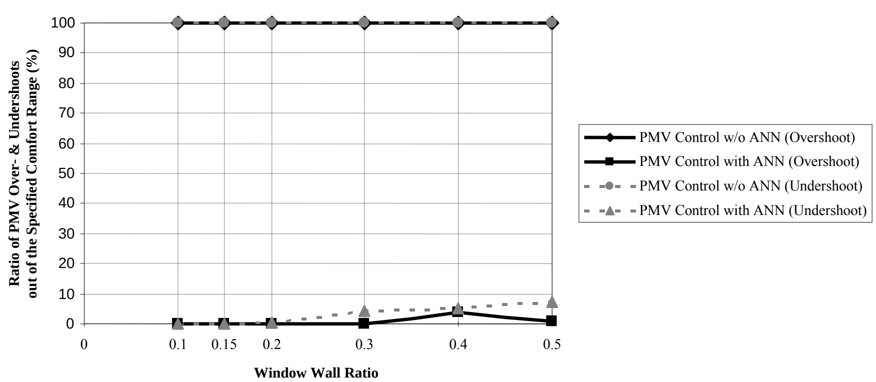

Figure 5.81 Comparison of the Ratio of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Increasing (Heating and Humidifying): Window Wall Ratio

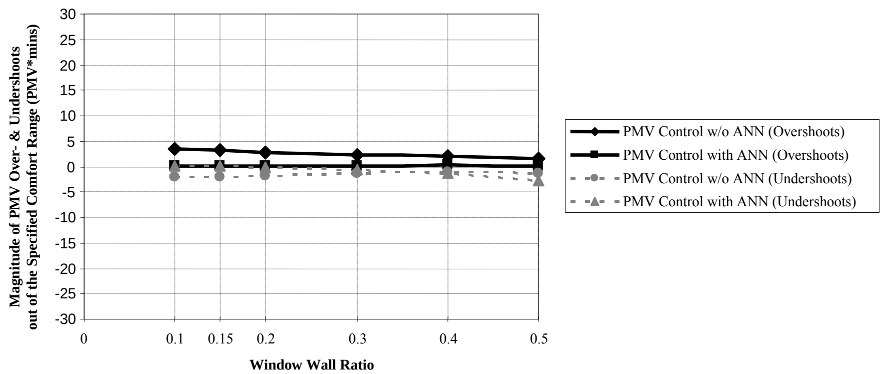

Figure 5.82 Comparison of the Magnitude of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Increasing (Heating and Humidifying): Window Wall Ratio

Summer

The ratios of overshoots and undershoots for air temperature were all 100.0% using the conventional logic, while those using the predictive logic were zero in most cases except for 0.4% (R5) for overshoots (Figure 5.83). Magnitudes using the predictive logic, as well, were all zero for R-values of the roof except for 0.03°C*minutes (R5) for overshoots (Figure 5.84). Those using the conventional logic ranged from 2.15°C*minutes for WWR0.4 to 3.17°C*minutes for WWR0.2 for overshoots and from -3.02°C*minutes for WWR0.5 to -6.86°C*minutes for WWR0.1 for undershoots. The features of overshoots and undershoots for air temperature for WWR can be concluded to be improved using the predictive control logic.

The ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0%, while those using the predictive logic were reduced to between 0.0% and 50.0% for undershoots in WWR0.1 and 0.2 (5 out of 10 each) (Figure 5.85). Magnitudes of shoots were reduced using the predictive logic in most cases (Figure 5.86). However, they increased using the predictive logic in some cases, for example, from -0.44 to -1.88%*minutes (WWR0.1) and from -1.28 to -11.37%*minutes (WWR0.2) for undershoots. As a result, the predictive logic generally demonstrates improvement in overshoots and undershoots for humidity but cannot be guaranteed for all cases.

As WWR increased, magnitudes of overshoots and undershoots increased rapidly using the conventional logic as WWR increased. The reason for the overshoot increase relates to the period when the air temperature began to rise in the morning. During this period, the humidity level with higher WWR was higher than that with lower WWR because the air temperature was maintained lower with higher WWR during the night. Therefore, when the cooling kicked in, the humidity easily went out of the specified comfort range because of the drop in temperature. In addition, the undershoot increase occurred during the daytime, when air temperature with the higher WWR building was easily raised because of heat gain through the envelope and solar radiation. Thus, in higher WWR buildings, humidity more easily falls below the specified comfort range even without dehumidifying. These two conditions create an increase in undershoots and overshoots with higher WWR cases.

Compared to the ratios of overshoots and undershoots for PMV using the PMV control without ANN, which were all 100.0%, the ratios using the PMV control with ANN improved significantly to between 0.0% and 14.7% for undershoots of WWR0.15 and 0.5 (Figure 5.87). Magnitudes were reduced for all R-values (Figure 5.88). Magnitude values using the PMV control without ANN were from 4.06 PMV*minutes (WWR0.1) to 8.26 PMV*minutes (WWR0.4) for overshoots and from -11.44 PMV*minutes (WWR0.5) to -18.22 PMV*minutes (WWR0.1) for undershoots. In contrast, those using PMV control with ANN fell between 0.00 PMV*minutes and -7.38 PMV*minutes (WWR0.15) for undershoots. Thus, PMV control with ANN significantly reduces the overshoots and undershoots for PMV.

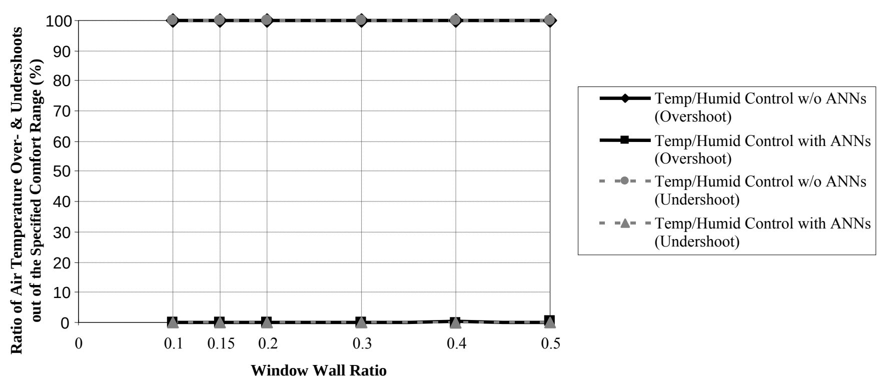

Figure 5.83 Comparison of the Ratio of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Cooling: Window Wall Ratio

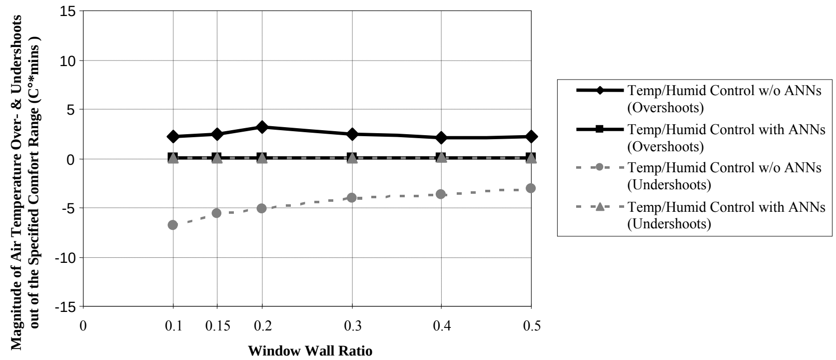

Figure 5.84 Comparison of the Magnitude of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Cooling: Window Wall Ratio

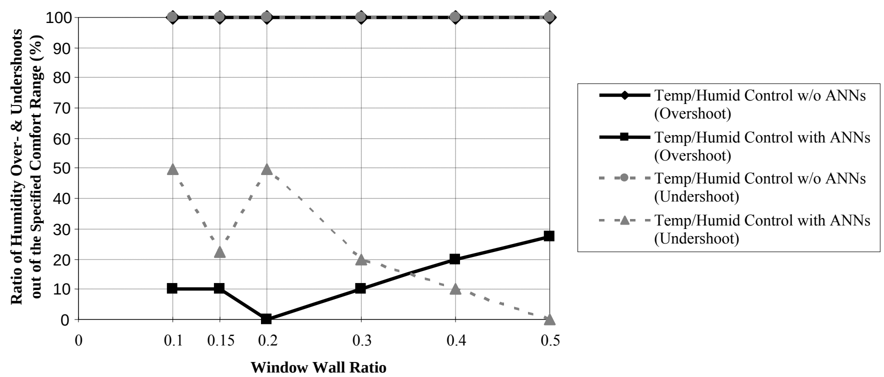

Figure 5.85 Comparison of the Ratio of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Dehumidifying: Window Wall Ratio

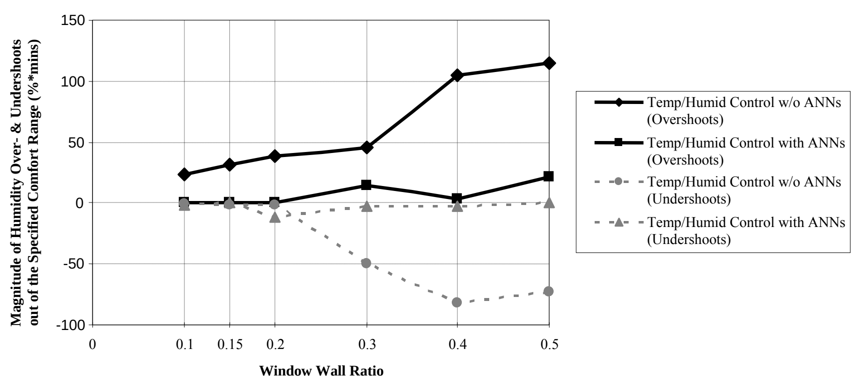

Figure 5.86 Comparison of the Magnitude of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Dehumidifying: Window Wall Ratio

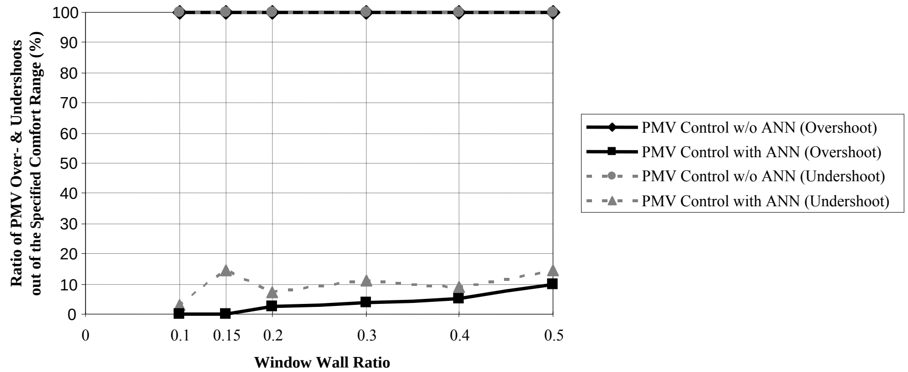

Figure 5.87 Comparison of the Ratio of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Decreasing (Cooling and Dehumidifying): Window Wall Ratio

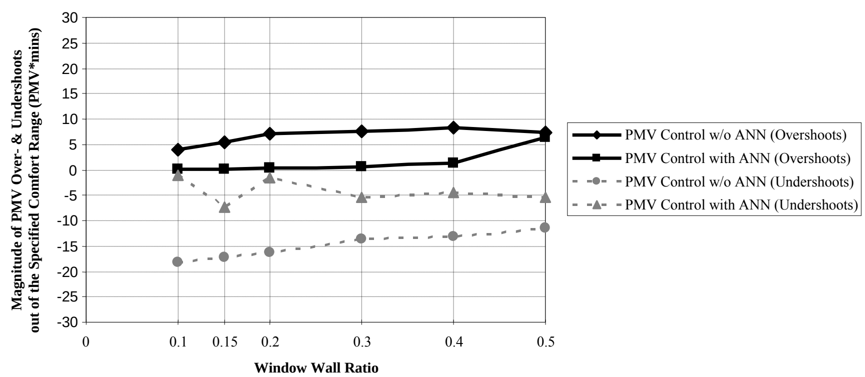

Figure 5.88 Comparison of the Magnitude of PMV Overshoots and Undershoots out of the Specified Comfort Range by PMV Decreasing (Cooling and Dehumidifying): Window Wall Ratio

f. Change of Internal Load

The ratios of overshoots and undershoots were all 100.0% using the conventional logic. In contrast, the ratios using the predictive logic were all zero, with the exception of 0.2% for overshoots of the heating device (Table 5.12). Therefore, magnitudes of shoots using the predictive logic were all reduced to 0.0 except for 0.06°C*minutes for overshoots of the heating device (Table 5.13). In contrast, the magnitudes of shoots using the conventional logic resulted in larger values, thus demonstrating the discomfort of air temperature. Based on these comparisons, the logic with the ANN model improved the stability of air temperature within the specified comfort range for the change of internal load.

The ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0% for the dehumidifying device while those using the predictive logic were significantly reduced to between 0.0 and 22.2% (Table 5.14). There were no requirements for humidifying when the internal load increased because of the increase in the internal moisture load. Magnitudes of shoots were also reduced using the predictive logic (Table 5.15). Therefore, the predictive control with the ANN model can be seen to control humidity conditions more properly than the conventional logic for the change of internal load.

Compared to the ratios of overshoots and undershoots for PMV using a logic without ANN, which were all 100.0%, the ratios using a logic with the ANN model improved significantly to between 0.0 to 17.5% (Table 5.16). Magnitudes of shoots were also reduced using PMV control with ANN (Table 5.17). As a result, PMV in the changed internal load is also better stabilized using the logic with the ANN model.

System Operation	Ratio of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating (Winter)	Ratio of Overshoots (%)	100.0	**0.2**
	Ratio of Undershoots (%)	100.0	**0.0**
Cooling (Summer)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**0.0**

Table 5.12 Ratio (%) of Overshoots and Undershoots out of the Specified Comfort Range: Air Temperature, Change of Internal Load

System Operation	Magnitude of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating (Winter)	Magnitude of Overshoots (˚C*minutes)	4.19	**0.06**
	Magnitude of Undershoots (˚C*minutes)	-5.27	**0.00**
Cooling (Summer)	Magnitude of Overshoots (˚C*minutes)	6.53	**0.00**
	Magnitude of Undershoots (˚C*minutes)	-5.92	**0.00**

Table 5.13 Magnitude (˚C*minutes) of Overshoots and Undershoots out of the Specified Comfort Range: Air Temperature, Change of Internal Load

System Operation	Ratio of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Humidifying (Winter)	Ratio of Overshoots (%)	-	-
	Ratio of Undershoots (%)	-	-
Dehumidifying (Summer)	Ratio of Overshoots (%)	100.0	**22.2**
	Ratio of Undershoots (%)	100.0	**0.0**

Table 5.14 Ratio (%) of Overshoots and Undershoots out of the Specified Comfort Range: Humidity, Change of Internal Load

System Operation	Magnitude of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Humidifying (Winter)	Magnitude of Overshoots (%*minutes)	-	-
	Magnitude of Undershoots (%*minutes)	-	-
Dehumidifying (Summer)	Magnitude of Overshoots (%*minutes)	21.30	**0.31**
	Magnitude of Undershoots (%*minutes)	-0.09	**0.00**

Table 5.15 Magnitude (%*minutes) of Overshoots and Undershoots out of the Specified Comfort Range: Humidity, Change of Internal Load

System Operation	Ratio of Shoots	PMV Control w/o ANN	PMV Control with ANN
PMV Increasing (Heating and Humidifying in Winter)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**0.6**
PMV Decreasing (Cooling and Dehumidifying in Summer)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**17.5**

Table 5.16 Ratio (%) of Overshoots and Undershoots out of the Specified Comfort Range: PMV, Change of Internal Load

System Operation	Magnitude of Shoots	PMV Control w/o ANN	PMV Control with ANN
PMV Increasing (Heating and Humidifying in Winter)	Magnitude of Overshoots (PMV*minutes)	6.64	**0.00**
	Magnitude of Undershoots (PMV*minutes)	-7.62	**-0.03**
PMV Decreasing (Cooling and Dehumidifying in Summer)	Magnitude of Overshoots (PMV*minutes)	18.44	**0.00**
	Magnitude of Undershoots (PMV*minutes)	-21.87	**-13.13**

Table 5.17 Magnitude (PMV*minutes) of Overshoots and Undershoots out of the Specified Comfort Range: PMV, Change of Internal Load

g. Change of Ventilation Rate

While the ratios of overshoots and undershoots for air temperature out of the specified comfort range were all 100.0% using the conventional logic, those using the predictive logic were all zero except for 0.3% for overshoots of the heating device (Table 5.18). In addition, compared to magnitudes using the conventional logic, those using the predictive logic were all reduced (Table 5.19). These comparisons clearly demonstrate the improvement using the ANN-based logic.

The ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0% for the dehumidifying device, but those using the predictive logic were all significantly reduced to between 0.0 and 11.1% (Table 5.20). Magnitudes of shoots were also reduced by the predictive logic (Table 5.21). Therefore, the humidity conditions are better controlled using the predictive control with the ANN model for the change of ventilation rate.

Compared to the ratios of overshoots and undershoots for PMV using the logic without ANN, which were all 100.0%, the ratios using the logic with the ANN model improved significantly to between 0.0 and 10.1% (Table 5.22). Magnitudes of shoots were also reduced using PMV control with ANN (Table 5.23). This result demonstrates that the PMV control with ANN better controls PMV within the specified comfort range than does PMV control without ANN for the changed ventilation rate.

System Operation	Ratio of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating (Winter)	Ratio of Overshoots (%)	100.0	**0.3**
	Ratio of Undershoots (%)	100.0	**0.0**
Cooling (Summer)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**0.0**

Table 5.18 Ratio (%) of Overshoots and Undershoots out of the Specified Comfort Range: Air Temperature, Change of Ventilation Rate

System Operation	Magnitude of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating (Winter)	Magnitude of Overshoots (˚C*minutes)	2.85	**0.04**
	Magnitude of Undershoots (˚C*minutes)	-4.60	**0.00**
Cooling (Summer)	Magnitude of Overshoots (˚C*minutes)	5.15	**0.00**
	Magnitude of Undershoots (˚C*minutes)	-6.13	**0.00**

Table 5.19 Magnitude (˚C*minutes) of Overshoots and Undershoots out of the Specified Comfort Range: Air Temperature, Change of Ventilation Rate

System Operation	Ratio of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Humidifying (Winter)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**0.0**
Dehumidifying (Summer)	Ratio of Overshoots (%)	100.0	**11.1**
	Ratio of Undershoots (%)	100.0	**0.0**

Table 5.20 Ratio (%) of Overshoots and Undershoots out of the Specified Comfort Range: Humidity, Change of Ventilation Rate

System Operation	Magnitude of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Humidifying (Winter)	Magnitude of Overshoots (%*minutes)	0.86	**0.00**
	Magnitude of Undershoots (%*minutes)	-0.82	**0.00**
Dehumidifying (Summer)	Magnitude of Overshoots (%*minutes)	642.39	**172.44**
	Magnitude of Undershoots (%*minutes)	-0.45	**0.00**

Table 5.21 Magnitude (%*minutes) of Overshoots and Undershoots out of the Specified Comfort Range: Humidity, Change of Ventilation Rate

System Operation	Ratio of Shoots	PMV Control w/o ANN	PMV Control with ANN
PMV Increasing (Heating and Humidifying in Winter)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**0.1**
PMV Decreasing (Cooling and Dehumidifying in Summer)	Ratio of Overshoots (%)	100.0	**0.4**
	Ratio of Undershoots (%)	100.0	**10.1**

Table 5.22 Ratio (%) of Overshoots and Undershoots out of the Specified Comfort Range: PMV, Change of Ventilation Rate

System Operation	Magnitude of Shoots	PMV Control w/o ANN	PMV Control with ANN
PMV Increasing (Heating and Humidifying in Winter)	Magnitude of Overshoots (PMV*minutes)	3.76	**0.00**
	Magnitude of Undershoots (PMV*minutes)	-6.51	**-0.01**
PMV Decreasing (Cooling and Dehumidifying in Summer)	Magnitude of Overshoots (PMV*minutes)	14.49	**0.02**
	Magnitude of Undershoots (PMV*minutes)	-21.82	**-5.09**

Table 5.23 Magnitude (PMV*minutes) of Overshoots and Undershoots out of the Specified Comfort Range: PMV, Change of Ventilation Rate

5.2.2.3 System Variables

Features of overshoots and undershoots were analyzed for the application of setback and change of setpoint.

a. Application of Setback

The ratios of overshoots and undershoots were all 100.0% using the conventional logic. In contrast, the ratios using the predictive logic were reduced to between zero and 2.8% (Table 5.24). The magnitudes of shoots using the predictive logic were all 0.0 except for -6.66 °C*minutes. On the other hand, the magnitudes of shoots using the conventional logic produced larger values demonstrating the more uncomfortable air temperature conditions produced by the heating and cooling devices (Table 5.25). This result indicates that the logic with the ANN model would maintain air temperature more properly within the specified comfort range for the application of setback.

The ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0% for a dehumidifying device while those using predictive logic were significantly reduced to 0.0 and 20% (Table 5.26). There were no requirements for humidifying under the setback mode. The magnitudes of shoots were also reduced using the predictive logic (Table 5.27). Therefore, the ANN-based control logic can be seen to control humidity conditions more comfortably within the specified comfort range.

Compared to the ratios of overshoots and undershoots for PMV using a logic without ANN, which were all 100.0%, the ratios using a logic with the ANN model improved significantly to between 0.9 to 60.9% (Table 5.28). Magnitudes of shoots were also reduced using PMV control with ANN (Table 5.29). As a result, it can be concluded that PMV will also stabilize better using the predictive control with the ANN model.

System Operation	Ratio of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating (Winter)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**2.8**
Cooling (Summer)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**0.0**

Table 5.24 Ratio (%) of Overshoots and Undershoots out of the Specified Comfort Range: Air Temperature, Application of Setback

System Operation	Magnitude of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating (Winter)	Magnitude of Overshoots (˚C*minutes)	1.89	**0.00**
	Magnitude of Undershoots (˚C*minutes)	-7.35	**-6.66**
Cooling (Summer)	Magnitude of Overshoots (˚C*minutes)	5.31	**0.00**
	Magnitude of Undershoots (˚C*minutes)	-7.67	**0.00**

Table 5.25 Magnitude (˚C*minutes) of Overshoots and Undershoots for out of the Specified Comfort Range: Air Temperature, Application of Setback

System Operation	Ratio of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Humidifying (Winter)	Ratio of Overshoots (%)	-	-
	Ratio of Undershoots (%)	-	-
Dehumidifying (Summer)	Ratio of Overshoots (%)	100.0	**20.0**
	Ratio of Undershoots (%)	100.0	**0.0**

Table 5.26 Ratio (%) of Overshoots and Undershoots out of the Specified Comfort Range: Humidity, Application of Setback

System Operation	Magnitude of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Humidifying (Winter)	Magnitude of Overshoots (%*minutes)	-	-
	Magnitude of Undershoots (%*minutes)	-	-
Dehumidifying (Summer)	Magnitude of Overshoots (%*minutes)	49.46	**1.79**
	Magnitude of Undershoots (%*minutes)	-0.04	**0.00**

Table 5.27 Magnitude (%*minutes) of Overshoots and Undershoots out of the Specified Comfort Range: Humidity, Application of Setback

System Operation	Ratio of Shoots	PMV Control w/o ANN	PMV Control with ANN
PMV Increasing (Heating and Humidifying in Winter)	Ratio of Overshoots (%)	100.0	**5.5**
	Ratio of Undershoots (%)	100.0	**0.9**
PMV Decreasing (Cooling and Dehumidifying in Summer)	Ratio of Overshoots (%)	100.0	**1.3**
	Ratio of Undershoots (%)	100.0	**60.9**

Table 5.28 Ratio (%) of Overshoots and Undershoots out of the Specified Comfort Range: PMV, Application of Setback

System Operation	Magnitude of Shoots	PMV Control w/o ANN	PMV Control with ANN
PMV Increasing (Heating and Humidifying in Winter)	Magnitude of Overshoots (PMV*minutes)	3.98	**2.51**
	Magnitude of Undershoots (PMV*minutes)	-7.54	**-0.46**
PMV Decreasing (Cooling and Dehumidifying in Summer)	Magnitude of Overshoots (PMV*minutes)	12.95	**1.11**
	Magnitude of Undershoots (PMV*minutes)	-24.82	**-9.02**

Table 5.29 Magnitude (PMV*minutes) of Overshoots and Undershoots out of the Specified Comfort Range: PMV, Application of Setback

b. Change of Setpoint

Features of overshoots and undershoots were analyzed for the diverse degrees of setpoint of the heating and cooling devices.

<u>Winter</u>

The ratios of overshoots and undershoots for air temperature were all 100.0% using the conventional logic, while those using the predictive logic were between zero, in most cases, and 2.0% for undershoots at a setpoint of 24.5°C for a heating device (Figure 5.89). Magnitudes using the predictive logic were all reduced to between zero and 2.10°C*minutes for overshoots at a setpoint of 18.5°C and between zero and -1.78°C*minutes for undershoots at a setpoint of 24.5°C (Figure 5.90). Those using the conventional logic were all larger from 3.16°C*minutes at a setpoint of 22.5°C to 4.57°C*minutes at a setpoint of 17.5°C for overshoots and from -4.74°C*minutes at a setpoint of 24.5°C to -6.20°C*minutes at a setpoint of 19.5°C for undershoots. Based on this comparison, the air temperature will be better stabilized better within the specified comfort range using the predictive control with the ANN model for the diverse setpoints.

The ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0%, while those using the predictive logic were all 0.0% (Figure 5.91). Magnitudes of shoots were reduced to 0.0% using the predictive logic in all cases (Figure 5.92). Those using the conventional logic were between 0.04 at a setpoint of 22.5°C and 0.19 %*minutes at a setpoint of 21.5°C for overshoots and between -0.01 at a setpoint of 22.5°C and -0.11%*minutes at a setpoint of 21.5°C for undershoots. As a result, the predictive logic demonstrates improved features of overshoots and undershoots for humidity.

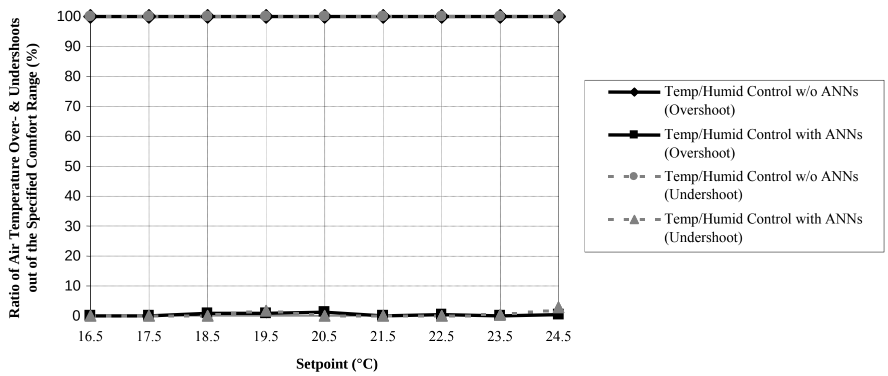

Figure 5.89 Comparison of the Ratio of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Heating: Setpoint

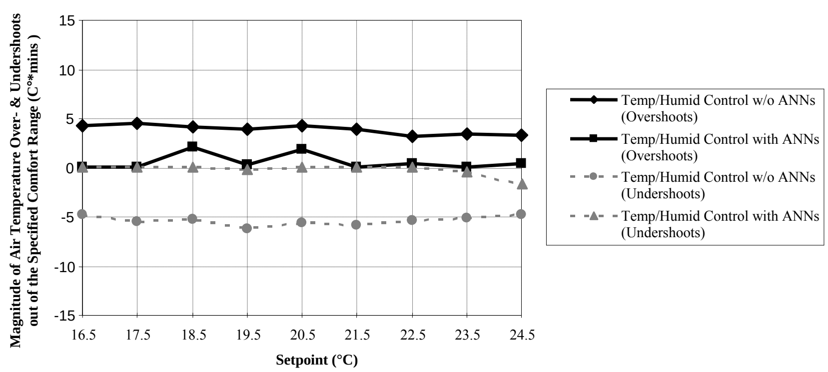

Figure 5.90 Comparison of the Magnitude of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Heating: Setpoint

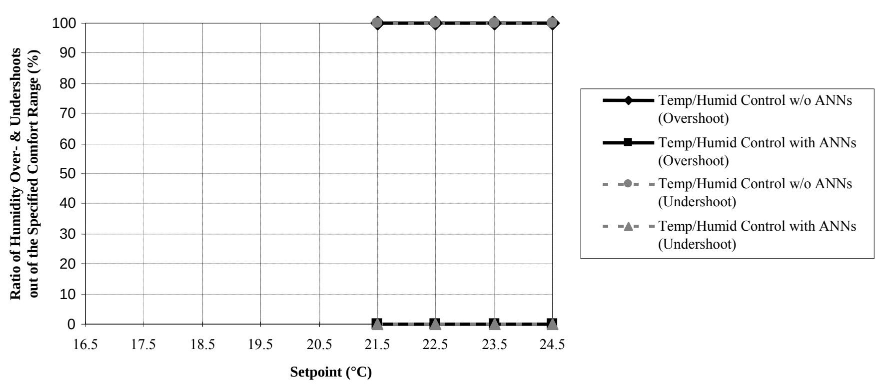

Figure 5.91 Comparison of the Ratio of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Humidifying: Setpoint

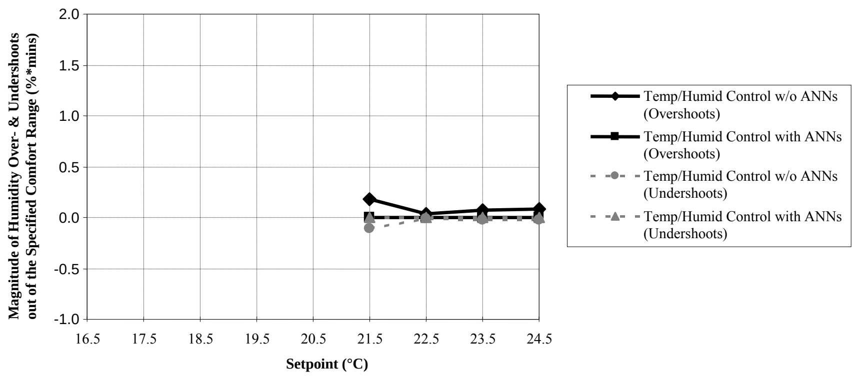

Figure 5.92 Comparison of the Magnitude of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Humidifying: Setpoint

Summer

The ratios of overshoots and undershoots for air temperature were all 100.0% using the conventional logic, while those using the predictive logic were zero in most cases except for 0.6% for overshoots at a setpoint of 25.5°C and 0.2% for undershoots at a setpoint of 21.5°C for a cooling device (Figure 5.93). Magnitudes using the predictive logic were all reduced to between zero and 1.63°C*minutes for overshoots at a setpoint of 21.5°C and between zero and -0.07°C *minutes for undershoots at a setpoint of 21.5°C (Figure 5.94). Those using the conventional logic were from 4.17°C*minutes at a setpoint of 26.5°C to 5.85°C*minutes at a setpoint of 23.5°C for overshoots and from -6.27°C*minutes at a setpoint of 26.5°C to -10.44°C*minutes at a setpoint of 21.5°C for undershoots. The overshoots and undershoots for air temperature for the change of setpoints will thus be reduced using the predictive control logic.

The ratios of overshoots and undershoots for humidity using the conventional logic were all 100.0%, while those using the predictive logic were between 0.0% and 40.0% for overshoots (4 out of 10 overshoots) at a setpoint of 25.5°C and 22.2% for undershoots (2 out of 9 undershoots) at a setpoint of 24.5°C (Figure 5.95). Magnitudes of shoots were reduced by the predictive logic in all cases to between zero to 5.15%*minutes at a setpoint of 25.5°C for overshoots and between zero to -0.84%*minutes at a setpoint of 25.5°C for undershoots (Figure 5.96). Those using the conventional logic were between 21.08%*minutes at a setpoint of 25.5°C and 40.35%*minutes at a setpoint of 26.5°C for overshoots and between -0.54%*minutes at a setpoint of 26.5°C and -1.85%*minutes at a setpoint of 21.5°C for undershoots. Thus, the predictive logic generally demonstrates improved features of overshoots and undershoots for humidity, but this is not true for all cases.

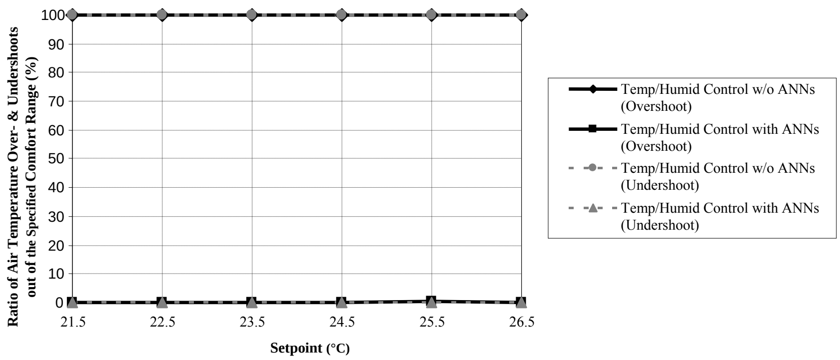

Figure 5.93 Comparison of the Ratio of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Cooling: Setpoint

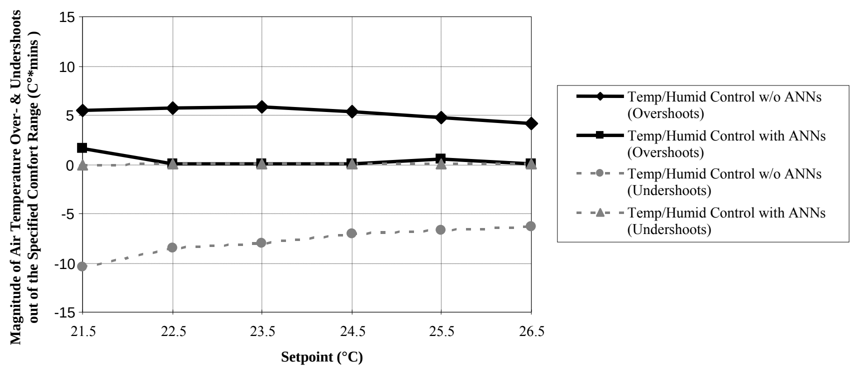

Figure 5.94 Comparison of the Magnitude of Air Temperature Overshoots and Undershoots out of the Specified Comfort Range by Cooling: Setpoint

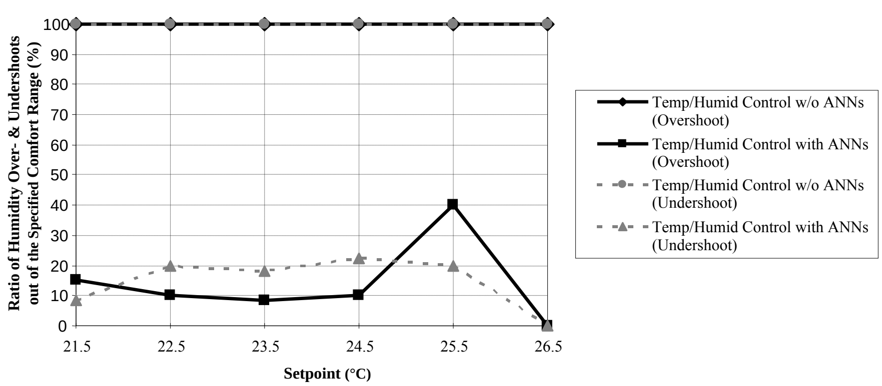

Figure 5.95 Comparison of the Ratio of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Dehumidifying: Setpoint

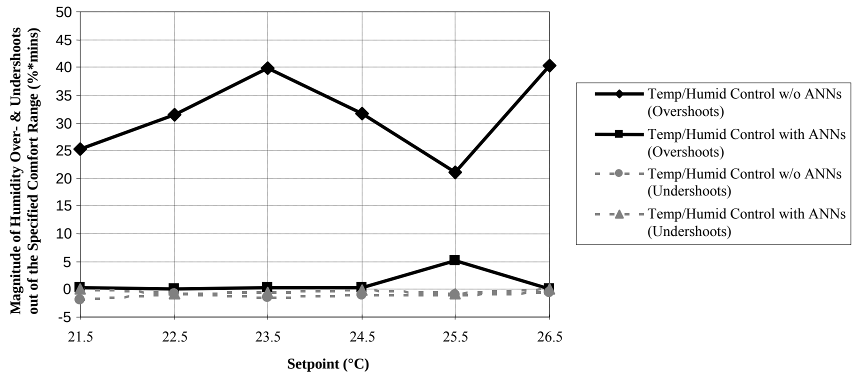

Figure 5.96 Comparison of the Magnitude of Humidity Overshoots and Undershoots out of the Specified Comfort Range by Dehumidifying: Setpoint

5.2.2.4 Exterior Climatic Variables

The ratios of overshoots and undershoots for air temperature were all 100.0% using the conventional logic. On the other hand, those using the predictive logic were all reduced to between 0.0% and 4.9% with the heating and cooling devices (Table 5.30). The predictive logic, however, did not clearly reduce the magnitudes of shoots compared to the conventional logic (Table 5.31). Magnitudes of undershoots with the heating and cooling devices increased slightly using the predictive logic, primarily as a result of the larger degree of undershoots in the early period of the simulation. Therefore, magnitudes increased even though the number of undershoots was lower. This phenomenon decreased as the simulation went on. Based on these results, the logic with the ANN model may show some discomfort in extremely changing climate conditions, but the discomfort can be stabilized after sufficient training. As no humidifying and dehumidifying were in operation, no ratios and magnitudes exist for humidity.

The ratios of overshoots and undershoots for PMV using the conventional logic were all 100.0%, while those using the predictive logic were all reduced to 0.0% (Table 5.32). Therefore, magnitudes of shoots were also reduced to 0.00 PMV*minutes using the predictive logic (Table 5.33). This result indicates that for the change of climate conditions, the predictive PMV control with the ANN model controls PMV conditions more properly than does the conventional logic.

System Operation	Ratio of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating	Ratio of Overshoots (%)	100.0	**0.9**
	Ratio of Undershoots (%)	100.0	**3.3**
Cooling	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**4.9**

Table 5.30 Ratio (%) of Overshoots and Undershoots out of the Specified Comfort Range: Air Temperature, Change of Climate Conditions

System Operation	Magnitude of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating	Magnitude of Overshoots (˚C*minutes)	2.02	**0.16**
	Magnitude of Undershoots (˚C*minutes)	**-2.14**	-2.42
Cooling	Magnitude of Overshoots (˚C*minutes)	0.36	**0.00**
	Magnitude of Undershoots (˚C*minutes)	**-1.15**	-1.50

Table 5.31 Magnitude (˚C*minutes) of Overshoots and Undershoots out of the Specified Comfort Range: Air Temperature, Change of Climate Conditions

System Operation	Ratio of Shoots	PMV Control w/o ANN	PMV Control with ANN
PMV Increasing (Heating and Humidifying)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**0.0**
PMV Decreasing (Cooling and Dehumidifying)	Ratio of Overshoots (%)	100.0	**0.0**
	Ratio of Undershoots (%)	100.0	**0.0**

Table 5.32 Ratio (%) of Overshoots and Undershoots out of the Specified Comfort Range: PMV, Change of Climate Conditions

System Operation	Magnitude of Shoots	PMV Control w/o ANN	PMV Control with ANN
PMV Increasing (Heating and Humidifying)	Magnitude of Overshoots (PMV*minutes)	3.85	**0.00**
	Magnitude of Undershoots (PMV*minutes)	-4.29	**0.00**
PMV Decreasing (Cooling and Dehumidifying)	Magnitude of Overshoots (PMV*minutes)	0.64	**0.00**
	Magnitude of Undershoots (PMV*minutes)	-1.85	**0.00**

Table 5.33 Magnitude (PMV*minutes) of Overshoots and Undershoots out of the Specified Comfort Range: PMV, Change of Climate Conditions

5.2.3 Energy Efficiency

The energy efficiency of each control logic for simulation variables was analyzed. The contents for analysis consisted of a comparison of the amount of heat supply (heating) and removal (cooling) and moisture supply (humidifying) and removal (dehumidifying) by control devices. These amounts are not exactly the same as the amount of energy, such as electricity or natural gas, required since the efficiency of devices was not considered in the simulation tool. Nonetheless, it is still worthwhile to compare these amounts (heat and moisture supply and removal) to investigate the improvement using the predictive logic.

5.2.3.1 Basecase

The ANN-based predictive logic saved energy in most device operations. It was not guaranteed, however, in all devices, such as humidifying in winter and cooling in summer using temperature and humidity control with ANNs (Table5.34). In these cases, 3.0% (from 13.3 to 13.7 Kg) more moisture was supplied and 0.1% (from 287.3 to 287.7 KWh) more heat was removed. In other cases, the control logic with the ANN models saved from 0.3% (from 255.0 to 254.3 KWh for cooling and from 60.2 to 60.0 Kg for dehumidifying using PMV control with ANN in summer) to 2.5% (from 151.4 to 147.6 Kg for dehumidifying using temperature and humidity control with ANNs) of device operations.

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.

From the analysis, it can be concluded that the effect of energy saving using the predictive control logic is not as significant as might be 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.

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 5.34 Comparison of Heating, Cooling (KWh), Humidifying, and Dehumidifying (Kg): Basecase

5.2.3.2 Architectural Variables

Energy efficiency was parametrically analyzed for the architectural variables: orientation, R-values for walls, the roof and windows, window wall ratio (WWR).

a. Orientation

As the orientation of the target building was rotated to the north, the amount of heating in winter increased while the amount of cooling in summer decreased (Figure 5.97). In addition, compared to the conventional logic, the predictive logic usually resulted in a decrease in heating. In addition, in most cases, the amount of cooling increased using the predictive logic, which means that the control logic using the ANN models could not guarantee a reduction in energy consumption. The same explanation from the basecase can be used here: the extra operating time for the cooling device using the conventional method was compensated for by the longer period of non-operation time. The amount of improvement was from 0.3% (from 735.6 to 733.5 KWh for West and from 712.1 to 710.3 KWh for South-West) to 0.9% (from 691.2 to 684.8 KWh for South, from 753.8 to 746.9 KWh for North, and from 755.3 to 748.7 KWh for North-West) for heating in winter and from -1.9% (from 238.2 to 242.8 KWh for East) to 0.8% (from 263.0 to 261.0 KWh for South-East) for cooling in summer. A negative value means an increase in device operations.

Similar to heating, the amount of humidifying and dehumidifying decreased in most cases but not all (Figure 5.98). The amount of improvement ranged from -4.8% (from 8.3 to 8.7 Kg for South-West) to 42.3% (from 13.0 to 7.5 Kg for South-East) for humidifying in winter and from -0.2% (from 150.7 to 151.0 Kg for North-West) to 4.8% (from 152.4 to 145.1 Kg for North) for dehumidifying in summer.

The amount of heating and humidifying for increasing PMV decreased in all cases, while the amount of cooling and dehumidifying for decreasing PMV increased in most cases using PMV control with ANN (Figures 5.9996 and 5.100). The amount of improvement in heating and humidifying went from 0.8% (from 759.0 to 745.2 KWh for heating and from 117.1 to 116.0 Kg for humidifying for South-East) to 1.4% (from 702.8 to 691.4 KWh for heating and from 110.1 to 108.3 Kg for humidifying for South) in winter. In addition, the amount of improvement of cooling and dehumidifying ranged from -2.8% (from 201.2 to 206.8 KWh for cooling and from 47.5 to 48.8 Kg for dehumidifying for North-West) to 0.6% (from 217.0 to 215.7 KWh for cooling and from 51.2 to 50.9 Kg for dehumidifying for West) in summer.

From these comparisons of device operations, it can be concluded that the logic with the ANN models is generally advantageous for reducing energy consumption, though it cannot be guaranteed for buildings in all orientations.

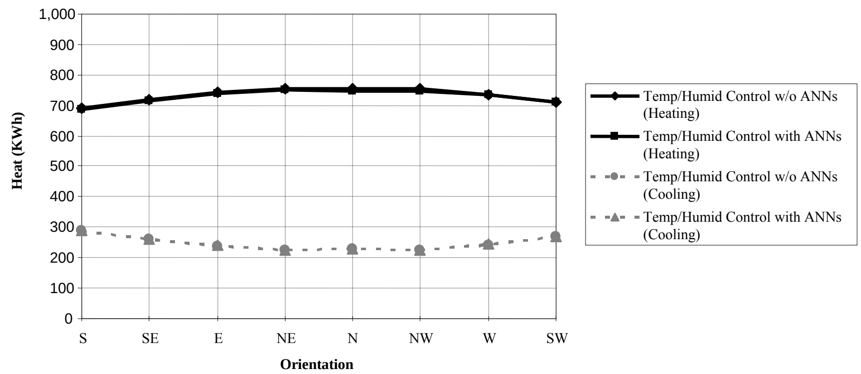

Figure 5.97 Comparison of the Amount of Heating and Cooling: Orientation

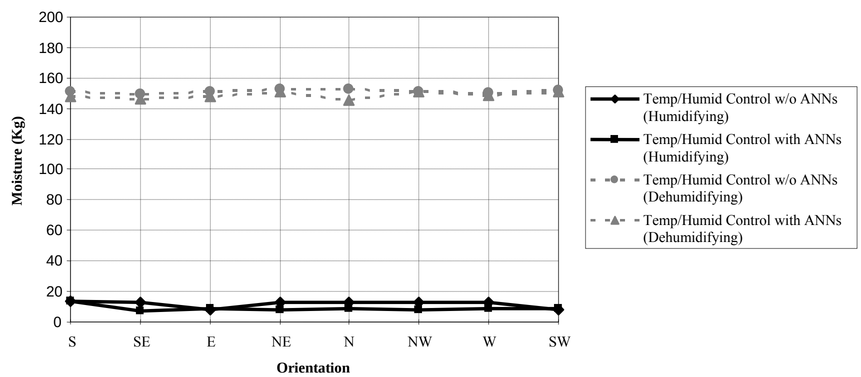

Figure 5.98 Comparison of the Amount of Humidifying and Dehumidifying: Orientation

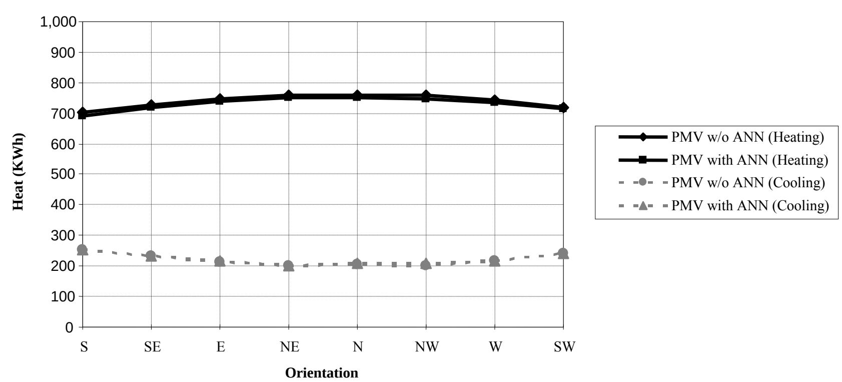

Figure 5.99 Comparison of the Amount of Heating and Cooling: Orientation

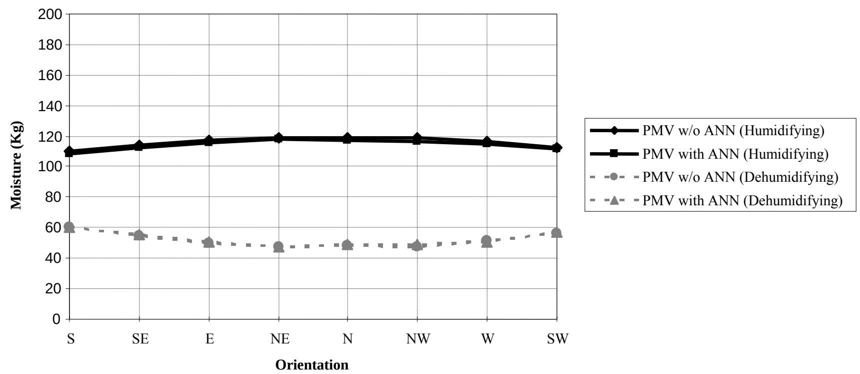

Figure 5.100 Comparison of the Amount of Humidifying and Dehumidifying: Orientation

b. R-values for Walls

As the R-value increased, the amount of heating and cooling decreased by both logics (Figure 5.101). However, the diminishing line became stabilize for higher R-values. Compared to the conventional logic, in most cases, the predictive logic slightly reduced the heating and cooling in most cases. The amount of improvement went from -0.1% (from 586.2 to 586.6 KWh for R50) to 0.9% (from 591.2 to 584.8 KWh for R19) for heating in winter and from -0.4% (from 274.8 to 276.0 KWh for R40, and from 272.2 to 273.3 KWh for R50) to 1.3% (from 304.3 to 300.2 KWh for R10) for cooling in summer.

As the R-value increased, the amount of dehumidifying decreased. But the level stabilized after R19 (Figure 5.102), meaning that any additional wall insulation beyond R19 would not provide significant economic benefit. The amount 0 Kg of humidifying meant that there was no humidifying process beyond R30 walls. Similar to the heating and cooling, in most cases, the amount of humidifying and dehumidifying was reduced by the predictive logic. The amount of improvement ranged from -3.0% (from 13.3 to 13.7 Kg for R19) to 6.7% (from 18.0 to 16.8 Kg for R15) for humidifying in winter and from -4.2% (from 144.4 to 150.5 Kg for R30) to 2.5% (from 151.2 to 147.6 Kg for R19) for dehumidifying in summer.

The PMV control with the ANN model reduced the amount of heating, cooling, humidifying, and dehumidifying in all cases (Figures 5.103 and 5.104). The amount of improvement in heating and humidifying for increasing PMV were from 0.3% (from 608.4 to 606.3 KWh for heating and from 95.3 to 95.0 Kg for humidifying for R40) to

1.6% (from 702.8 to 691.4 KWh for heating and from 110.1 to 108.3 Kg for humidifying for R19) in winter. In addition, the amount of improvement in cooling and dehumidifying for PMV decreasing were 0.1% (from 244.2 to 244.0 KWh for cooling and from 57.62 to 57.58 Kg for dehumidifying for R50) to 2.6% (from 249.7 to 243.3 KWh for cooling and from 58.9 to 57.4 Kg for dehumidifying for R30) in summer.

From the comparions of the amount of devices operation, it can be concluded that although energy consumption generally decreased using the ANN-based logics, it may not always be guaranteed for all levels of wall insulation.

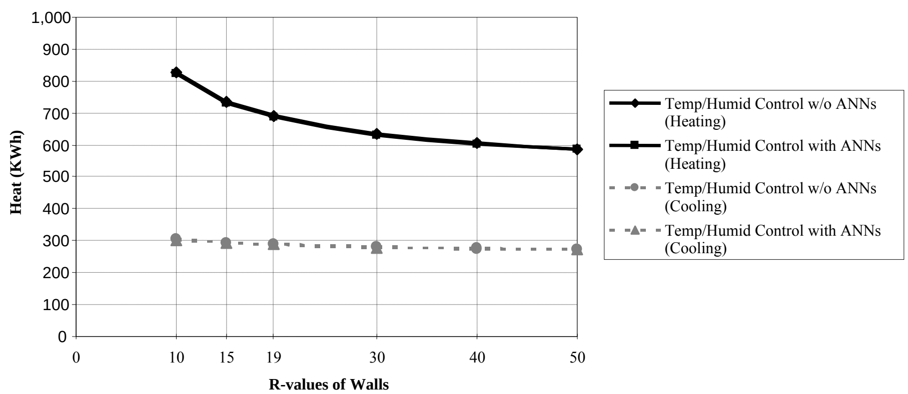

Figure 5.101 Comparison of the Amount of Heating and Cooling: R-value for Walls

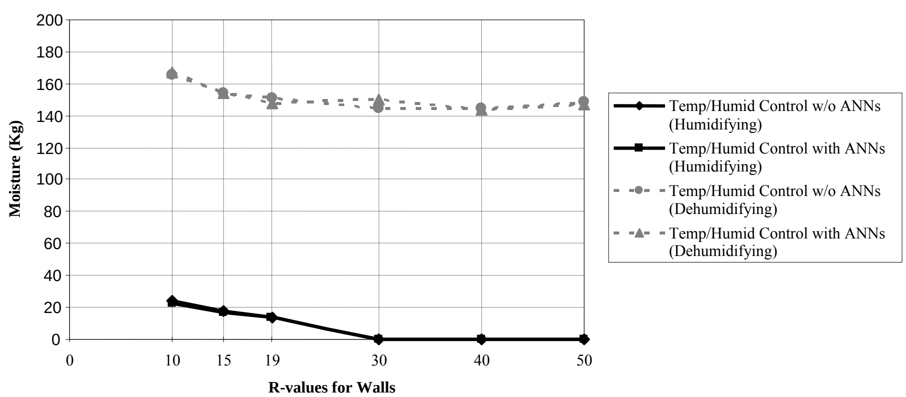

Figure 5.102 Comparison of the Amount of Humidifying and Dehumidifying: R-value for Walls

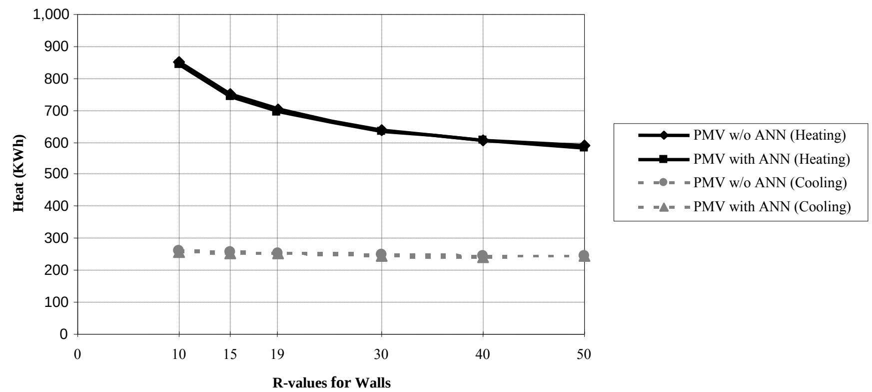

Figure 5.103 Comparison of the Amount of Heating and Cooling: R-value for Walls

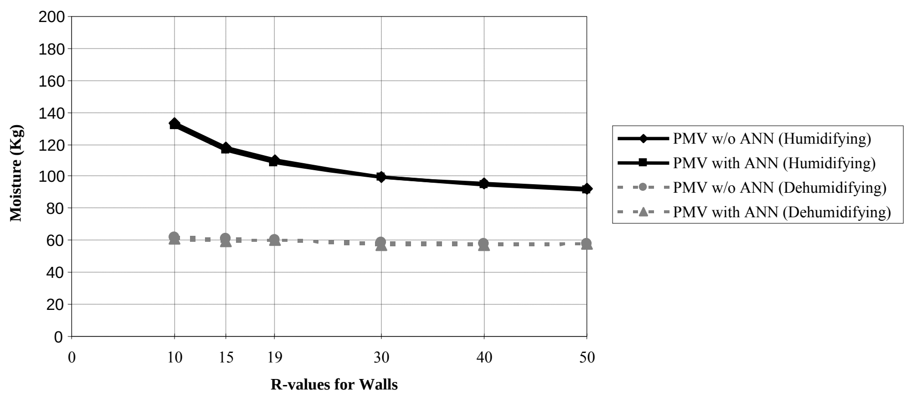

Figure 5.104 Comparison of the Amount of Humidifying and Dehumidifying: R-value for Walls

c. R-values for the Roof

As the R-value increased, the amount of heating and cooling decreased and stabilized beginning around R38 (Figure 5.105). Compared to the conventional logic, the predictive logic slightly reduced the heating in all cases and the cooling in most cases. The amount of improvement was from 0.1% (from 576.2 to 575.5 KWh for R60, and from 565.4 to 564.7 KWh for R80) to 1.2% (from 591.0 to 583.0 KWh for R40) for heating in winter and from -0.6% (from 284.7 to 286.3 KWh for R60) to 1.1% (from 294.0 to 290.7 KWh for R20) for cooling in summer.

Similar to heating and cooling, in most cases, the amount of humidifying and dehumidifying was reduced by the predictive logic (Figure 5.106). The amount of improvement ranged widely from -3.0% (from 13.3 to 13.7 Kg for 38R) to 100.0% (from 6.4 to 0.0 Kg for R60, from 6.5 to 0.0 Kg for R70, and from 7.1 to 0.0 Kg for R80) for humidifying in winter and from -3.5% (from 155.3 to 160.8 Kg for R10) to 7.0% (from 151.7 to 141.1 Kg for R60) for dehumidifying in summer. The improvement to 100.0% in winter meant that there was no humidifying operation by the predictive logic.

The PMV control with the ANN model decreased the amount of heating and humidifying in all cases, while it increased the amount of cooling and dehumidifying in many cases (Figures 5.107 and 5.108). The amount of improvement in heating and humidifying for increasing PMV went from 0.6% (from 678.8 to 675.0 KWh for heating and from 106.3 to 105.8 Kg for humidifying for 70) to 2.6% (from 700.4 to 682.1 KWh for heating and from 109.7 to 106.9 Kg for humidifying for R40) in winter. The amount of improvement in cooling and dehumidifying for PMV decreasing were -1.6% (from 263.7 to 267.8 KWh for cooling and from 62.2 to 63.2 Kg for dehumidifying for R10) to 0.3% (from 255.0 to 254.3 KWh for cooling and from 60.2 to 60.0 Kg for dehumidifying for R38) in summer.

For the diverse levels of the roof insulation, the predictive control logic with the ANN models showed energy efficiency in most cases, though there were some exceptions. It can therefore be concluded that the predictive control logic does not always guarantee economic benefits.

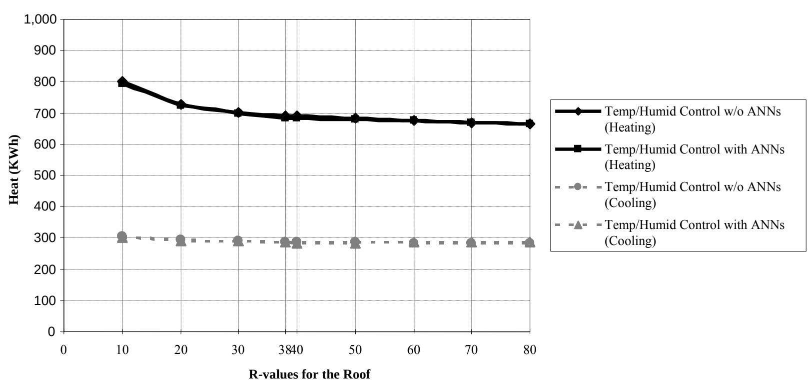

Figure 5.105 Comparison of the Amount of Heating and Cooling: R-value for the Roof

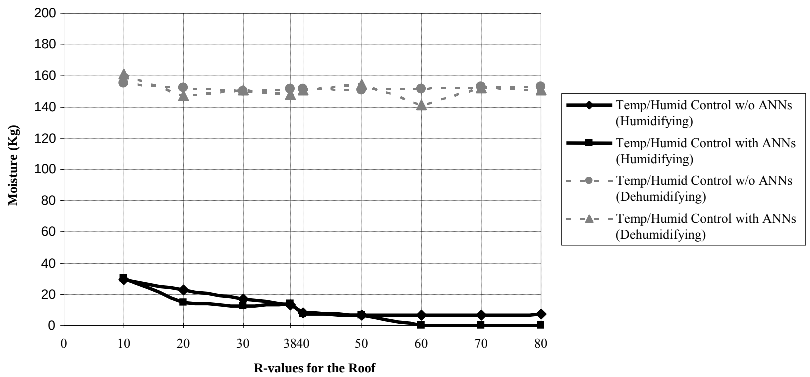

Figure 5.106 Comparison of the Amount of Humidifying and Dehumidifying: R-value for the Roof

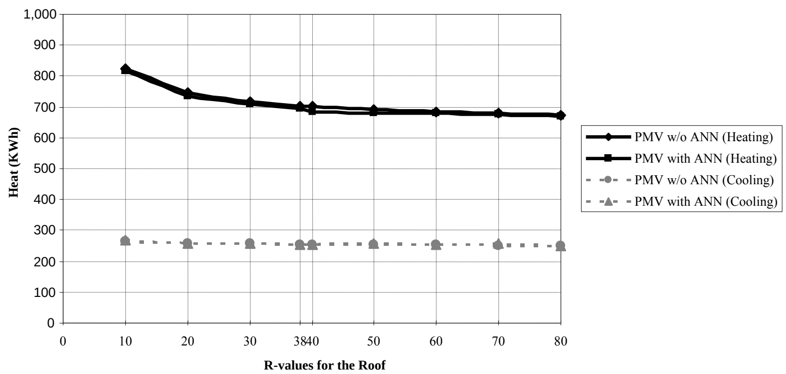

Figure 5.107 Comparison of the Amount of Heating and Cooling: R-value for the Roof

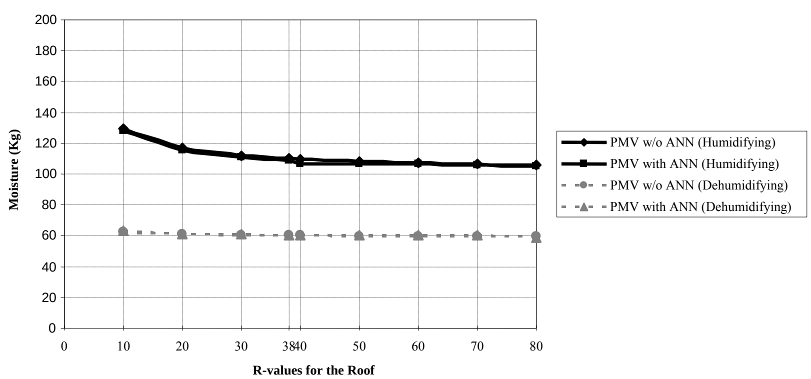

Figure 5.108 Comparison of the Amount of Humidifying and Dehumidifying: R-value for the Roof

d. R-values for Windows

As the R-value increased, the amount of heating decreased significantly while that of cooling did not significantly change (Figure 5.109), which means that the increase in the insulating level for windows would be economically beneficial in a cold climate.

Compared to the conventional logic, in most cases, the predictive logic slightly reduced the heating and cooling. The amount of improvement was from -0.9% (from 494.9 to 499.4 KWh for R9) to 1.4% (from 483.0 to 476.0 KWh for R10) for heating in winter and from -0.1% (from 287.3 to 287.7 KWh for R3.44) to 1.6% (from 281.2 to 276.8 KWh for R10) for cooling in summer.

Similar to heating and cooling, in most cases, the amount of humidifying and dehumidifying was reduced by the predictive logic (Figure 5.110). The amount of improvement ranged from -36.3% (from 13.5 to 18.4 Kg for R10) to 46.2% (from 15.6 to 8.4 Kg for R7) for humidifying in winter and from -0.8% (from 151.7 to 152.9 Kg for R7) to 7.1% (from 153.6 to 142.7 Kg for R10) for dehumidifying in summer.

The PMV control with the ANN model reduced the amount of heating and humidifying in all cases, while it reduced the amount of cooling and dehumidifying in most cases (Figures 5.111 and 5.112). The amount in improvement of heating and humidifying for increasing PMV was from 0.3% (from 621.9 to 619.5 KWh for heating and from 97.4 to 97.1 Kg for humidifying for R5) to 1.5% (from 668.6 to 658.8 KWh for heating and from 104.7 to 103.2 Kg for humidifying for R4) in winter. In addition, the amount of improvement in cooling and dehumidifying for PMV decreasing went from -1.2% (from 256.3 to 259.3 KWh for cooling and from 60.5 to 61.2 Kg for dehumidifying for R6) to 0.9% (from 255.2 to 253.0 KWh for cooling and from 60.2 to 59.7 Kg for dehumidifying for R4) in summer.

The comparison of device operations indicates that the predictive control logic is economically beneficial in most cases but can not be guaranteed for all levels of window insulation.

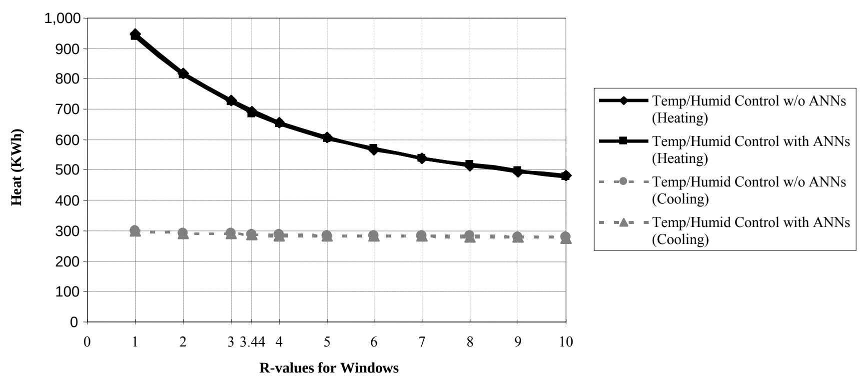

Figure 5.109 Comparison of the Amount of Heating and Cooling: R-value for Windows

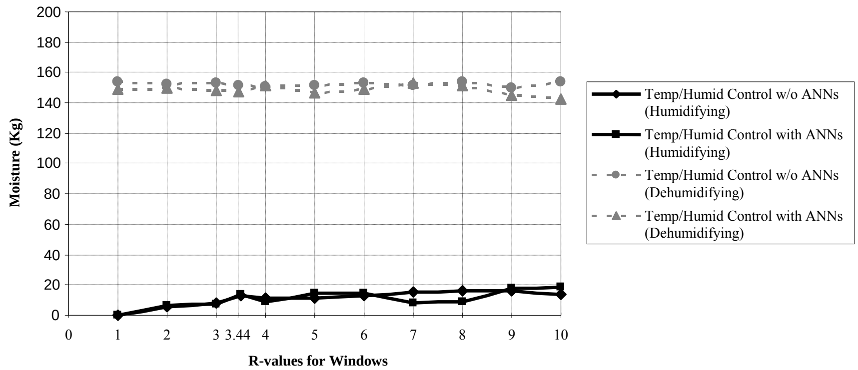

Figure 5.110 Comparison of the Amount of Humidifying and Dehumidifying: R-value for Windows

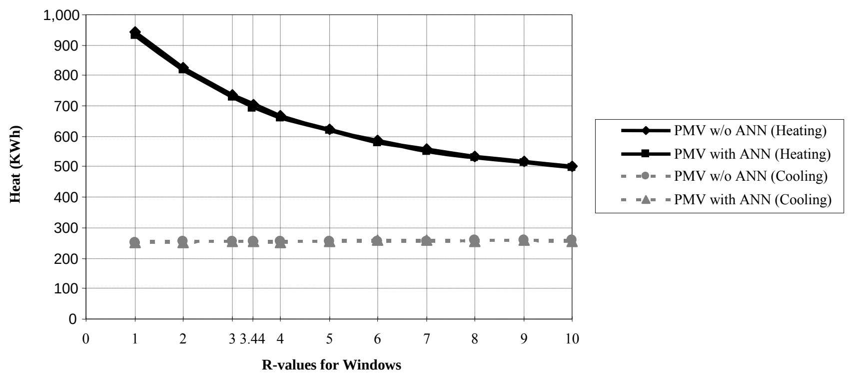

Figure 5.111 Comparison of the Amount of Heating and Cooling: R-value for Windows

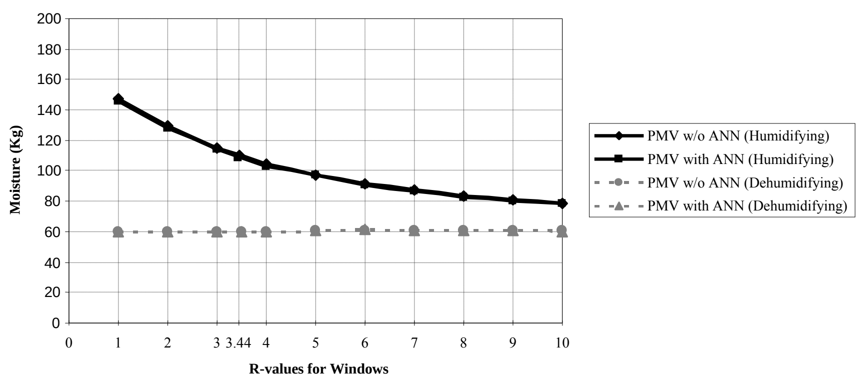

Figure 5.112 Comparison of the Amount of Humidifying and Dehumidifying: R-value for Windows

e. Window Wall Ratio

As the WWR increased, the amount of heating and cooling increased by both control logics (Figure 5.113). This increase was due to the increased heat loss in winter and heat gain in summer in a higher WWR building. Compared to the conventional logic, in most cases, the predictive logic slightly reduced the heating and cooling. The amount of improvement was from -0.6% (from 617.3 to 621.0 KWh for WWR0.1) to 0.9% (from 691.2 to 684.8 KWh for WWR0.15) for heating in winter and from -0.8% (from 460.7 to 464.2 KWh for WWR0.5) to 1.6% (from 328.8 to 323.7 KWh for WWR0.2, and from 396.3 to 390.0 KWh for WWR0.3) for cooling in summer.

In most cases, the amount of humidifying and dehumidifying was reduced by the predictive logic (Figure 5.114). The amount of improvement ranged from -37.0% (from 5.4 to 7.4 Kg for WWR0.2) to 25.0% (from 12.0 to 9.0 Kg for WWR0.1) for humidifying in winter and from -1.9% (from 149.2 to 152.1 Kg for WWR0.1) to 2.7% (from 142.4 to 138.5 Kg for WWR0.5) for dehumidifying in summer.

The PMV control with the ANN model reduced the amount of heating and humidifying in all cases but reduced the amount of cooling and dehumidifying in most cases (Figures 5.115 and 5.116). The amount of improvement in heating and humidifying for increasing PMV went from 0.5% (from 950.3 to 945.6 KWh for heating and from 148.9 to 148.1 Kg for humidifying for WWR0.5) to 1.8% (from 632.1 to 620.7 KWh for heating and from 99.0 to 97.2 Kg for humidifying for WWR0.1) in winter. In addition, the amount of improvement in cooling and dehumidifying for decreasing PMV was -0.1% (from 376.2 to 376.5 KWh for cooling and from 88.8 to 88.9 Kg for dehumidifying for WWR0.4) to 1.9% (from 225.5 to 221.3 KWh for cooling and from 52.5 to 51.5 Kg for dehumidifying for WWR0.1) in summer.

In a conclusion, the predictive logic with the ANN models generally showed a decrease in device operations, but this effect did not always occur at all levels of WWR.

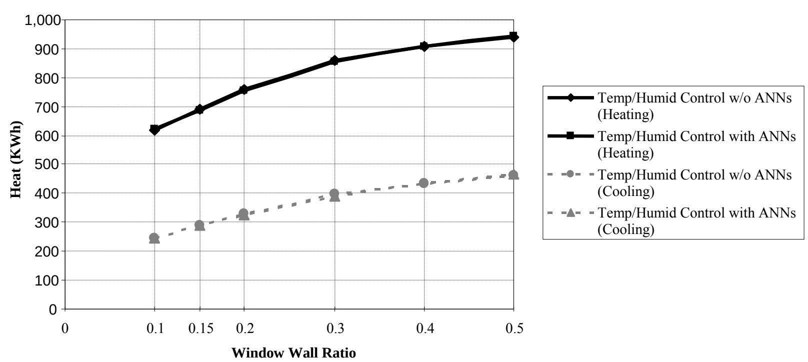

Figure 5.113 Comparison of the Amount of Heating and Cooling: Window Wall Ratio

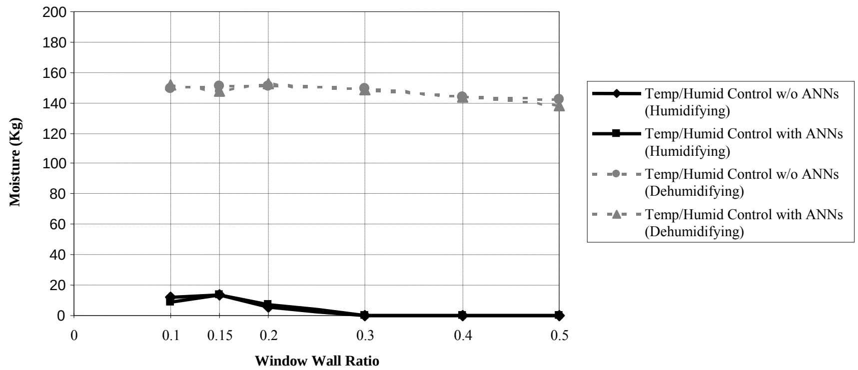

Figure 5.114 Comparison of the Amount of Humidifying and Dehumidifying: Window Wall Ratio

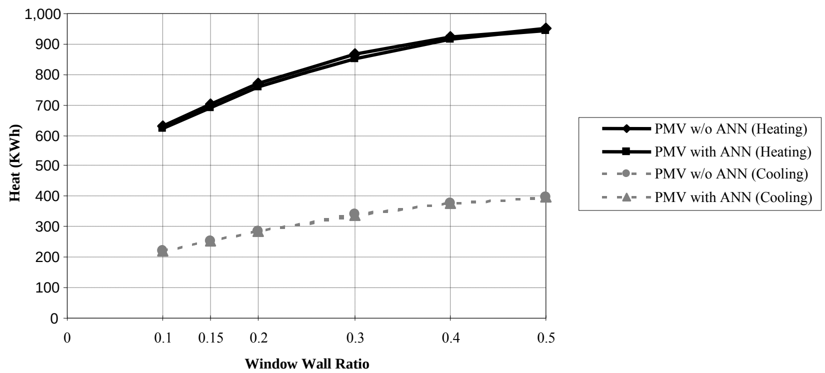

Figure 5.115 Comparison of the Amount of Heating and Cooling: Window Wall Ratio

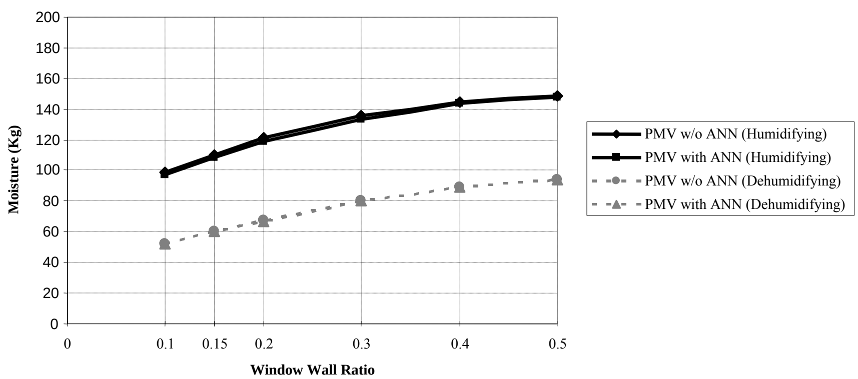

Figure 5.116 Comparison of the Amount of Humidifying and Dehumidifying: Window Wall Ratio

f. Change in Internal Load

The logic without the ANN models and with the ANN models showed similar results for device operations in the case of changed internal load (Table 5.35). The savings using the logic with the ANN models were from -2.8% (from 172.7 to 177.6 Kg for dehumidifying using temperature and humidity control with ANNs in summer) to 1.2% (from 627.0 to 619.2 KWh for heating and from 98.2 to 97.0 for humidifying using PMV control with ANN in winter). The results show that the logic with the ANN models could not guarantee energy savings for the changed internal load.

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)	623.0	**618.8**	627.0	**619.2**
	Humidifying (Kg)	0.0	0.0	98.2	**97.0**
Summer	Cooling (KWh)	360.7	**357.7**	**328.7**	330.7
	Dehumidifying (Kg)	**172.7**	177.6	**77.6**	78.0

Table 5.35 Comparison of Heating, Cooling (KWh), Humidifying, and Dehumidifying (Kg): Change of Internal Load

g. Change in Ventilation Rate

Logics with or without ANN models did not show a superiority of energy efficiency (Table 5.36). The savings using the predictive logic went from -6.0% (from 65.4 to 69.3 Kg for humidifying using temperature and humidity control with ANNs in winter) to 1.2% (from 823.4 to 813.2 KWh for heating and from 129.0 to 127.4 for humidifying using PMV control with ANN in winter). The results indicated that the logic with the ANN models could not guarantee energy savings for the changed ventilation rate.

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)	788.4	**785.6**	823.4	**813.2**
	Humidifying (Kg)	**65.4**	69.3	129.0	**127.4**
Summer	Cooling (KWh)	299.2	**296.3**	**258.5**	260.3
	Dehumidifying (Kg)	176.6	**176.5**	**61.0**	61.4

Table 5.36 Comparison of Heating, Cooling (KWh), Humidifying, and Dehumidifying (Kg): Change of Ventilation Rate

5.2.3.3 System Variables

Energy efficiency using the control logics was investigated for the application of setback and change of setpoint.

a. Application of Setback

Compared to the logic without the ANN models, the predictive logic with the ANN models saved heating, humidifying, cooling, and dehumidifying energy in both seasons (Table 5.37). The control logic with the ANN models saved from 0.4% (from 236.2 to 235.3 KWh for cooling and from 55.7 to 55.5 Kg for dehumidifying using PMV control with ANN in summer) to 2.4% (from 118.4 to 115.6 Kg for dehumidifying using temperature and humidity control with ANNs in summer) of device operations.

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**

Table 5.37 Comparison of Heating, Cooling (KWh), Humidifying, and Dehumidifying (Kg): Application of Setback

b. Change in Setpoint

As the setpoint went higher, the amount of heating increased while the amount of cooling decreased (Figure 5.117). In addition, these amounts shown by both the conventional logic and the predictive logic were similar in both seasons. Savings using the predictive logic were from -0.9% (from 535.8 to 540.6 KWh for setpoint 17.5°C) to 1.2% (from 797.7 to 788.4 KWh for setpoint 24.5°C) for heating in winter and from

-1.0% (from 223.8 to 226.0 KWh for setpoint 26.5°C) to 1.3% (from 393.7 to 388.7 KWh for setpoint 21.5°C) cooling in summer.

Similar to the heat supply and remove, the amounts of humidifying increased while those of dehumidifying decreased as the setpoint went higher (Figure 5.118). This phenomenon resulted from the relationship between air temperature and humidity. As the air temperature rises, the humidity level drops down. Thus, as the setpoint went higher, more humidifying was required in winter, but less dehumidifying was required in summer. In addition, the amounts of saving using the predictive logic were from -3.0% (from 13.3 to 13.7 Kg for setpoint 21.5°C) to 5.1% (from 31.4 to 29.8 Kg for setpoint 23.5°C) for humidifying in winter and from -0.3% (from 179.4 to 180.0 for setpoint 22.5°C) to 2.5% (from 151.4 to 147.6 Kg for setpoint 24.5°C) for dehumidifying in summer. Comparison of device operations shows that the logic with the ANN models did not result in a significant benefit for all setpoints for the devices operation.

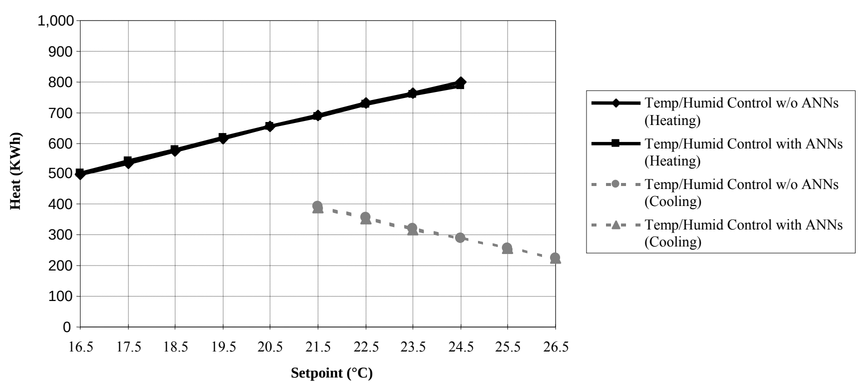

Figure 5.117 Comparison of the Amount of Heating and Cooling: Change of Setpoint

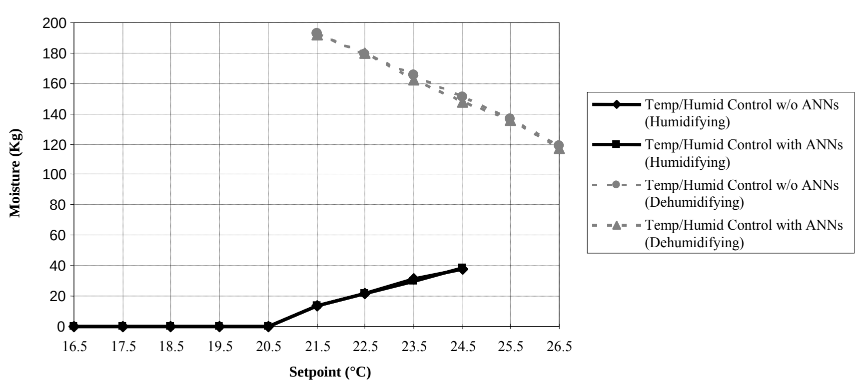

Figure 5.118 Comparison of the Amount of Humidifying and Dehumidifying: Change of Setpoint

5.2.3.4 Exterior Climatic Variables

The predictive control logic demonstrated advanced results in energy savings for most, but not all, cases (Table 5.38). The savings using the predictive logic were from -8.5% (from 42.2 to 45.8 Kg for cooling using temperature and humidity control with ANNs in summer) to 2.4% (from 521.7 to 509.3 KWh for heating using temperature and humidity control with ANNs in winter). Based on these results, the control logic with the ANN models is mostly advantageous for saving energy in climate conditions undergoing abnormal changes.

System Operations	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs	PMV Control w/o ANN	PMV Control with ANN
Heating (KWh)	521.7	**509.3**	525.6	**521.9**
Humidifying (Kg)	0.0	0.0	82.3	**81.8**
Cooling (KWh)	**42.2**	45.8	50.8	**50.3**
Dehumidifying (Kg)	0.0	0.0	12.0	**11.9**

Table 5.38 Comparison of Heating, Cooling (KWh), Humidifying, and Dehumidifying (Kg): Change of Climate Conditions

5.3 The Experiment

The experiment in the thermal chamber was conducted as the secondary method for testing the performance of the control logic for variables such as basecase and the application of setback mode for control devices.

5.3.1 Thermal Comfort

Thermal comfort using the control logic was investigated in terms of air temperature, humidity, and PMV.

5.3.1.1 Basecase

The result of each control logic was extracted for comparison for the period that had the most similar enthalpy conditions of exterior and surrounding interior spaces . The average enthalpies of exterior and surrounding spaces were summarized for both seasons (Table 5.39). Lengths of the sampled period were 38 hours in winter and 48 hours in summer.

Compared to the temperature and humidity control without ANNs (the conventional logic), temperature and humidity control with ANN (the predictive logic) improved the comfort period of air temperature (from 69.8% to 86.8%) and slightly humidity (from 97.3% to 97.6%) in winter but not significantly in summer (Table 5.40). This difference is reasonable because the heating device in winter was a radiant system that had a significant time lag, while the cooling system was an A/C that worked as soon as the device was turned on. In addition, improvement of humidity comfort period in winter, which was 0.3% increase, may not certainly prove the superioriy of the predictive logic because there could be some sensor errors (i.e., ±2% error by the employed humidity sensor). In order to reduce errors of monitored sensor data, normal averaging method, which makes the averaged value using more frequently monitored samples than required, needs to be applied in the future research. This method can attenuate signal fluctuation or noise, and flatten out peaks in the input signal. For examply, humidity is monitored at every second for one minute, and 60 samples are averaged for representing the humidity of that one minute. Using this method, errors of sensor data can be reduced.

Since PMV was the target to be controlled for, PMV control with the ANN model worked better to control PMV conditions (74.6% in winter and 15.8% in summer) than the temperature- and humidity-based control logic. On the other hand, the comfort periods of air temperature and humidity decreased because air temperature and humidity values were generally maintained higher than the specified comfort ranges in order to keep PMV comfortable. In addition, the low percentage of PMV comfort periods in summer (15.8%) was due to the cold interior conditions even without the operation of A/C and the dehumidifier.

		Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs	PMV Control with ANN
Winter	Exterior	7.24	7.23	7.31
	Surrounding Interior	18.08	17.65	17.79
		(Dec.19, 1am ~ Dec.20, 15pm, 2007)	(Dec.28, 1am ~ Dec.29, 15pm, 2007)	(Dec.31, 1am, 2007 ~ Jan.01, 15pm, 2008)
Summer	Exterior	16.76	16.78	16.76
	Surrounding Interior	19.51	19.54	19.53
		(Aug.11, 0am ~ Aug.12, 24pm, 2008)	(Aug.14, 0am ~ Aug.15, 24pm, 2008)	(Jun.24, 0am ~ Jun.25, 24pm, 2008)

Table 5.39 Average Enthalpy (Btu / lb of dry air) of Exterior and Surrounding Interior Space for Each Experimental Case: Basecase

Season	Specified Comfort Ranges	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs	PMV Control with ANN
Winter	Air Temperature (20~23˚C)	69.8	**86.8**	61.9
	Humidity (30~45%)	97.3	**97.6**	37.4
	PMV (-0.5~0.0)	38.6	33.6	**74.6**
Summer	Air Temperature (23~26˚C)	98.3	98.3	86.3
	Humidity (45~60%)	100.0	100.0	96.3
	PMV (0.0~0.5)	1.3	1.3	**15.8**

Table 5.40 Interior Air Temperature, Humidity and PMV Comfort Period (%):Basecase

5.3.1.2 Application of Setback

The average enthalpies of exterior and surrounding spaces for a sampled period were summarized; the length of the sampling period for each case was 24 hours and 8 hours in winter and summer, respectively (Table 5.41).

For the application of setback mode, the ANN-based predictive logic showed improvement in control of air temperature and humidity (Table 5.42). The comfort periods of air temperature increased from 89.6 to 97.0% for the setback period and from 81.0% to 82.3% for the normal period in winter. The overall period was also improved from 86.2% to 91.3% using the predictive logic. In contrast, those in summer was less significant than in winter, so that the overall comfort period of air temperature increased by 0.3%. Though not significant, the humidity conditions also improved, from 98.0% to

98.2% in winter. These insignificant improvements (0.3% for air temperature and 0.2% for humidity), however, may not certainly prove the advantages of the predictive logic due potential errors of sensor output (i.e., ±0.5°C for air temperature sensor and ±2% for humidity sensor). As explained in the basecase, normal averaging method is required in the future research for reducing sensor errors. Thus, this data analysis indicates that the predictive control with the ANN models controls air temperature more comfortably in winter than the conventional logic when a setback mode is applied for the control devices.

Similar to the basecase, PMV control with the ANN model worked better to control PMV conditions (85.3% in winter and 58.7% in summer) than the temperature- and humidity-based control logic for setback application. The comfort periods of air temperature and humidity decreased for the same reason as with the basecase.

		Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs	PMV Control with ANN
Winter	Exterior	7.00	6.78	6.94
	Surrounding Interior	17.68	17.70	17.80
		(Jan.17, 0am ~ 24pm, 2008)	(Jan.14, 0am ~ 24pm, 2008)	(Jan.28, 0am ~ 24pm, 2008)
Summer	Exterior	20.48	20.75	21.47
	Surrounding Interior	19.45	19.93	19.31
		(Jul.18, 16pm ~ 24pm, 2008)	(Aug.22, 16pm ~ 24pm, 2008)	(Aug.03, 16pm ~ 24pm, 2008)

Table 5.41 Average Enthalpy (Btu / lb of dry air) of Exterior and Surrounding Interior Space for Each Experimental Case: Application of Setback

Season	Specified Comfort Ranges		Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs	PMV Control with ANN
Winter	Air Temperature	15~18 (°C)	89.6	**97.0**	83.8
		20~23 (°C)	81.0	**82.3**	60.3
		Overall	86.2	**91.3**	74.8
	Humidity	30~45 (%)	98.0	**98.2**	66.5
	PMV	-2.0~-1.5	32.4	35.7	**83.9**
		-0.5~0.0	37.3	32.3	**87.8**
		Overall	34.2	34.5	**85.3**
Summer	Air Temperature	23~26 (°C)	93.1	**93.4**	31.3
	Humidity	45~60 (%)	100.0	100.0	2.2
	PMV	0.0~0.5	4.2	3.9	**58.7**

Table 5.42 Interior Air Temperature, Humidity and PMV Comfort Period (%): Application of Setback

5.3.2 Features of Overshoots and Undershoots out of the Specified Comfort Ranges

The ratios and magnitudes of overshoots and undershoots out of the specified comfort range were compared for the conventional logic (temperature and humidity control without ANNs) and the predictive logic (temperature and humidity control with ANNs).

5.3.2.1 Basecase

The ratios of overshoots and undershoots for air temperature using the conventional logic were all 100.0%, while those using the predictive logic were reduced in most cases except for the ratio of overshoots in summer, where the ratio did not improve (Table 5.43). In this case, every overshoot went out of the specified comfort range. The first reason for this was the insignificant time lag of A/C, which meant that the predictive control based on the ANN model was less effective in reducing overshoots. The second reason might be the higher enthalpy conditions of the exterior and surrounding space during the experimental period of the predictive logic. A higher enthalpy conditions can still raise the interior air temperature more easily at the moment when, or shortly after, the A/C is turned on. This higher enthalpy conditions also seems to affect the reduced ratio of undershoots using the predictive logic. For these reasons, the magnitude of overshoots in summer increased using the predictive logic (Table 5.44).

Compared to the conventional logic, the predictive logic reduced the ratio and magnitude of overshoots and undershoots for humidity in winter (Tables 5.45 and 5.46). However, it was impossible to compare those for a dehumidifying device since there were no dehumidifying operations.

System Operation	Ratio of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating (Winter)	Ratio of Overshoots (%)	100.0	**87.1**
	Ratio of Undershoots (%)	100.0	**87.1**
Cooling (Summer)	Ratio of Overshoots (%)	100.0	100.0
	Ratio of Undershoots (%)	100.0	**82.4**

Table 5.43 Ratio (%) of Overshoots and Undershoots for Air Temperature out of the Specified Comfort Range: Basecase

System Operation	Magnitude of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating (Winter)	Magnitude of Overshoots (˚C*minutes)	260.74	**48.12**
	Magnitude of Undershoots (˚C*minutes)	-26.08	**-19.71**
Cooling (Summer)	Magnitude of Overshoots (˚C*minutes)	**5.49**	7.58
	Magnitude of Undershoots (˚C*minutes)	-8.95	**-7.39**

Table 5.44 Magnitude (˚C*minutes) of Overshoots and Undershoots for Air Temperature out of the Specified Comfort Range: Basecase

System Operation	Ratio of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Humidifying (Winter)	Ratio of Overshoots (%)	100.0	**86.4**
	Ratio of Undershoots (%)	100.0	**86.4**
Dehumidifying (Summer)	Ratio of Overshoots (%)	-	-
	Ratio of Undershoots (%)	-	-

Table 5.45 Ratio (%) of Overshoots and Undershoots for Humidity out of the Specified Comfort Range: Basecase

System Operation	Magnitude of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Humidifying (Winter)	Magnitude of Overshoots (%*minutes)	13.87	**9.14**
	Magnitude of Undershoots (%*minutes)	-13.28	**-8.33**
Dehumidifying (Summer)	Magnitude of Overshoots (%*minutes)	-	-
	Magnitude of Undershoots (%*minutes)	-	-

Table 5.46 Magnitude (%*minutes) of Overshoots and Undershoots for Humidity out of the Specified Comfort Range: Basecase

5.3.2.2 Application of Setback

The ratios of overshoots and undershoots for air temperature were reduced using the predictive logic (Table 5.47). However, magnitude of overshoots in summer increased slightly using the ANN-based logic (Table 5.48), for the same reasons as with the basecase.

The logic with ANN models improved the ratio and magnitude of overshoots and undershoots for humidity (Tables 5.49 and 5.50). Similar to the basecase, there were no dehumidifying processes during the experimental periods.

System Operation	Ratio of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating (Winter)	Ratio of Overshoots (%)	100.0	**66.7**
	Ratio of Undershoots (%)	100.0	**88.9**
Cooling (Summer)	Ratio of Overshoots (%)	100.0	**75.0**
	Ratio of Undershoots (%)	100.0	**83.3**

Table 5.47 Ratio (%) of Overshoots and Undershoots for Air Temperature out of the Specified Comfort Range: Application of Setback

System Operation	Magnitude of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Heating (Winter)	Magnitude of Overshoots (˚C*minutes)	29.43	**9.21**
	Magnitude of Undershoots (˚C*minutes)	-10.34	**-9.17**
Cooling (Summer)	Magnitude of Overshoots (˚C*minutes)	**1.80**	2.03
	Magnitude of Undershoots (˚C*minutes)	-3.66	**-2.75**

Table 5.48 Magnitude (˚C*minutes) of Overshoots and Undershoots for Air Temperature out of the Specified Comfort Range: Application of Setback

System Operation	Ratio of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Humidifying (Winter)	Ratio of Overshoots (%)	100.0	**85.7**
	Ratio of Undershoots (%)	100.0	**85.7**
Dehumidifying (Summer)	Ratio of Overshoots (%)	-	-
	Ratio of Undershoots (%)	-	-

Table 5.49 Ratio (%) of Overshoots and Undershoots for Humidity out of the Specified Comfort Range: Application of Setback

System Operation	Magnitude of Shoots	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs
Humidifying (Winter)	Magnitude of Overshoots (%*minutes)	5.99	**5.39**
	Magnitude of Undershoots (%*minutes)	-2.55	**-2.06**
Dehumidifying (Summer)	Magnitude of Overshoots (%*minutes)	-	-
	Magnitude of Undershoots (%*minutes)	-	-

Table 5.50 Magnitude (%*minutes) of Overshoots and Undershoots for Humidity out of the Specified Comfort Range: Application of Setback

5.3.2 Energy Efficiency

The amount of electricity for heating, cooling, humidifying and dehumidifying was compared for investigating the energy efficiency of the control logic.

5.3.2.1 Basecase

Compared to the conventional logic, the predictive logic saved energy for heating (from 21,350 to 21,200 Wh) and humidifying (from 1,042 to 762 Wh) devices in winter while consuming more electricity for cooling (from 832 to 919 Wh) in summer. The increase during summer may be due to two factors: (1) no time lag by the A/C device and (2) higher enthalpy in the exterior and interior surrounding space when the predictive logic was tested (Table 5.51).

PMV control with ANN consumed more energy in both seasons than temperature- and humidity-based control logic. In winter, the specified comfort range of PMV is generally higher than those of air temperature and humidity; therefore the PMV-based control logic requirs more heating and humidifying operation and results in more energy consumption. On the other hand, the reason of the increased energy consumption in summer was due to the narrow range of PMV comfort. The specified comfort ranges of PMV were -0.5~0.0 in winter and 0.0~0.5. When a PMV was over 0.5 in summer, A/C and dehumidifying devices worked to cool down the interior air. When PMV reached 0.0, devices were turned off. However, PMV was still apt to go down a certain degree to reach -0.5, which was a marginal level required heating and humidifying to increase PMV. In this way, an unnecessary heating and humidifying process was underway causing additional energy consumption. Therefore, a function must be added to the algorithm to prevent the unnecessary operation of devices.

Season	System Operations	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs	PMV Control with ANN
Winter	Heating (Wh)	21,350	**21,200**	27,025
	Humidifying (Wh)	1,047	**762**	1,802
Summer	Cooling (Wh)	**832**	919	563
	Dehumidifying (Wh)	0	0	278
	Heating (Wh)	0	0	525
	Humidifying (Wh)	0	0	35

Table 5.51 The Amount of Heating, Cooling (KWh), Humidifying, and Dehumidifying (Kg): Basecases

5.3.2.2 Application of Setback

Compared to the conventional logic, the predictive logic consumed less energy for heating (from 10,425 to 9,250 Wh) and humidifying (from 300 to 258 Wh) devices in winter but more energy for cooling (from 862 to 949 Wh) in summer. The energy increase for cooling was due to the decreased time lag of the cooling device and the higher enthalpy conditions of the exterior and surrounding space during the experimental period of the predictive logic.

On the other hand, PMV control with ANN consumed more energy in both seasons than the temperature- and humidity-based control logic (Table 5.52). In winter, it was due to the same reason as the basecase. In summer, however, extra energy was consumed by the PMV-based control logic for dehumidification in the process for decreasing PMV.

Season	System Operations	Temp/Humid Control w/o ANNs	Temp/Humid Control with ANNs	PMV Control with ANN
Winter	Heating (Wh)	10,425	**9,250**	12,775
	Humidifying (Wh)	300	**258**	852
Summer	Cooling (Wh)	**862**	949	823
	Dehumidifying (Wh)	0	0	593

Table 5.52 The Amount of Heating, Cooling (KWh), Humidifying, and Dehumidifying (Kg): Application of Setback

CHAPTER VI

CONCLUSIONS

This study proposed the advanced thermal control method for residential buildings and examined their performance. The findings are based on results from the computer simulation and the experiment.

6.1 Thermal Comfort

- Data analysis revealed that ANN-based predictive control logic (temperature and humidity control with ANNs) controlled air temperature and humidity better within the specified comfort ranges than did the conventional logic. The increasing amounts of comfort period (%) were between 0.0% and 17.0% for air temperature and 0.0% and 11.6% for humidity. Based on this result, it can be concluded that the predictive control with the ANN models is advantageous for controlling air temperature and humidity comfortably.
- However, in a couple of exceptional cases, the comfort periods for air temperature and humidity decreased using the predictive logic. The decrease of comfort period was due to the inaccurate predictions in the early period of the simulation (first and second day), which did not recur beyond day three as a result of training. This result indicates that the predictive control logic with ANN models requires a sufficient period of training to avoid improper prediction.
- Two control logics having PMV as a control variable improved interior PMV conditions compared to the control logics for air temperature and humidity. In addition, the comfort period of PMV increased using the predictive logic (PMV control with ANN), somewhere between 0.0% and 12.4%. However, similar to

the air temperature and humidity control logics, an exceptional case decreasing the comfort period occurred due to the insufficient training. Therefore, a sufficient training process is required for reducing inaccurate predictions.

- For residential buildings in cold climate such as Detroit, Michigan, envelopes need to be sufficiently insulated for maintaining interior thermal conditions comfortably. R19 for walls, R38 for the roof, and R3.44 for windows are recommendable based on the fact that the increasing amount of comfort period for air temperature and PMV was significant up to those insulation levels, and any additional insulation did not significantly contribute to increasing comfort period. In addition, large window area over WWR0.15 is not recommendable due to the decrease of comfort periods by the heat gain in summer and loss in winter.

6.2 Features of Overshoots and Undershoots out of the Specified Comfort Ranges

- The predictive control logic with ANN models reduced the ratio and magnitude of overshoots and undershoots out of the specified comfort ranges for most variables of the computer simulation and the experiment. This result indicates that the predictive thermal controls stabilized air temperature, humidity, or PMV better within the specified comfort ranges.
- However, exceptional cases occurred, which increased the ratio and magnitude of overshoots and undershoots. In simulation, it was also due to the inaccurate predictions in the early simulation period. Again, the ANN model requires sufficient training before application. On the other hand, in the experiment, overshoots of air temperature increased in summer because of the higher enthalpy of exterior and surrounding interior condition during experimental periods for the predictive control logic.

6.3 Energy Efficiency

- The predictive control logic (temperature and humidity control with ANNs and PMV control with ANN) reduced energy consumption for most variables;

however, its amount was not as significant as expected. This was primarily due to the time compensation between operating and non-operating time. For example, the operating and non-operating times of a heating device in a cycle were shorter by the predictive logic because it predetermined the device operation. Thus, the frequency of the device turning on and off using the predictive logic was larger than the conventional 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.

- The PMV-based control logics consumed more energy in winter while less energy in summer compared to the temperature- and humidity-based control logics. This result was due to the higher specified comfort ranges for PMV than those for temperature and humidity. Upon this higher comfort ranges, PMV control logics required more heating and humidifying in winter, but less cooling and dehumidifying in summer. Based on this analysis, a study for investigating the priority between thermal comfort and energy efficiency, especially in winter season, needs to be conducted.

6.4 Conclusions

Data analysis revealed that the predictive logic with ANN models improved thermal comfort in terms of the comfort period (%) with reduced ratio and magnitude of overshoots and undershoots out of the specified comfort ranges for almost all the cases. Even in the exceptional cases, overshoots and undershoots using the logic with ANN models diminished as the test periods proceeded. Energy consumption generally decreased though not as significantly as expected in the hypothesis. Based on this study, it can be concluded that ANN-based predictive and adaptive climate control strategies can improve thermal comfort in residential buildings.

APPENDIX

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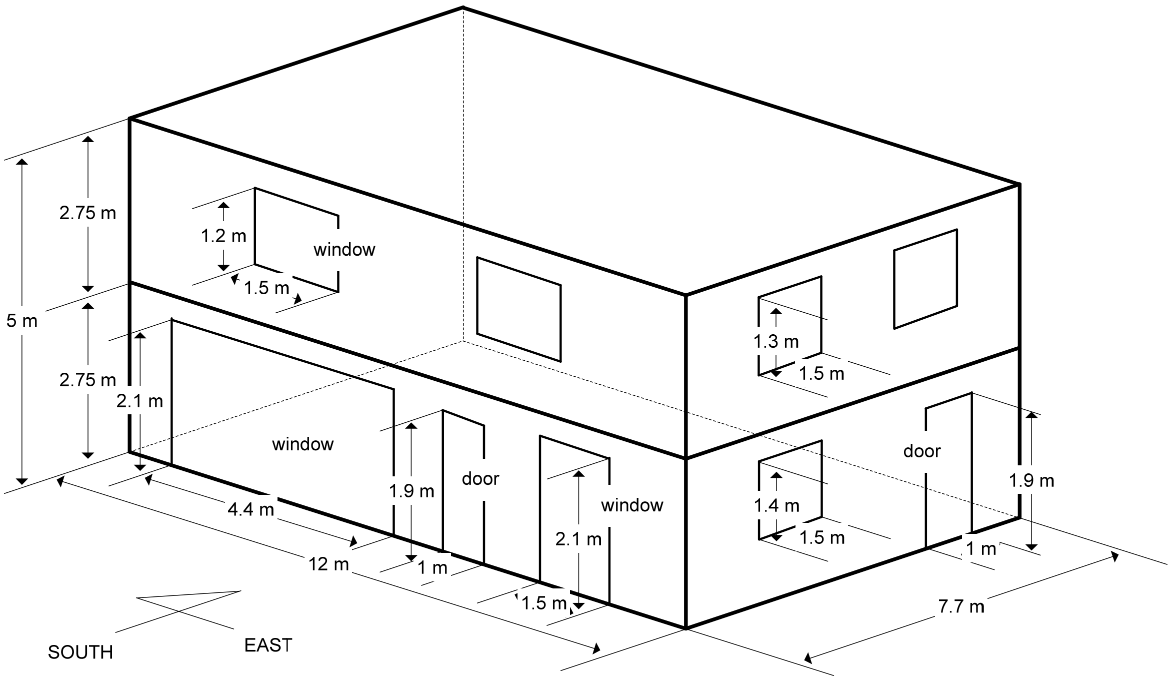
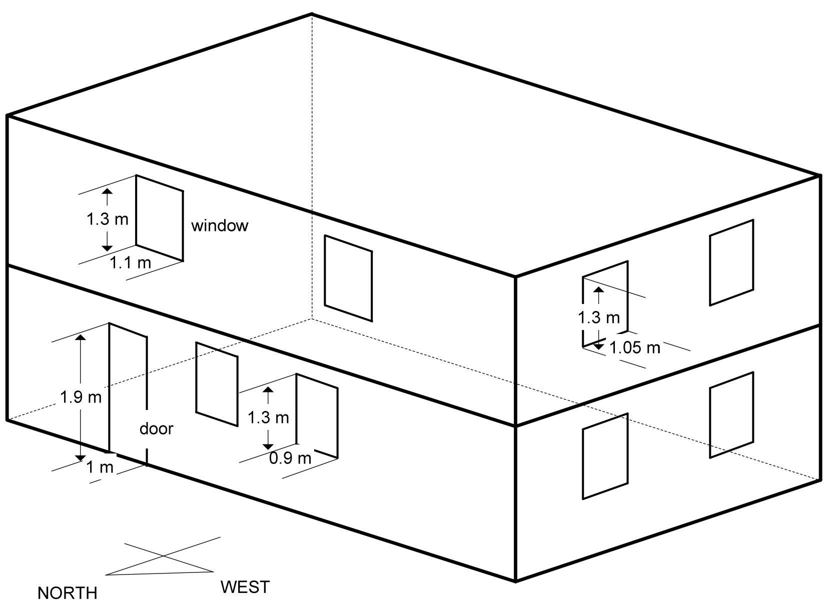
APPENDIX A

Input of the Computer Simulation





Views of a Target Building from South-East (left) and North-West (right)

1. Target Building

- South-facing 2-story residential building
- Area: 184.4m^2 (≈2,000ft^2)
- Volume: 508.2m^3
- R-values of envelope
  - R3.346 (R19 U.S.) walls: wood siding (0.019m) / cellulose (0.125m) / wooden panel (0.013m)
  - R6.692 (R38 U.S.) roof: roof deck (0.029m) / cellulose (0.255m) / wooden panel (0.016m)
  - R3.698 (R21 U.S.) floor: cellulose (0.133m) / timber flooring (0.052m)
  - R0.606 (R3.44 U.S.) windows: clear glass (0.00635m (1/4in)) / air / clear glass (0.00635m),
SC: 0.79, ST: 0.53, VT: 0.72)
  - R0.215 (R1.22) doors
- Surface heat transfer coefficient
  - Inside: 8.4 W/m^2*K for walls, windows and doors (R0.68 U.S.)
9.3 W/m^2*K for roof (R0.61 U.S.)
6.2 W/m^2*K for floor (R0.92 U.S.)
  - Outside: 40.5 W/m^2*K for walls and roof for winter (R0.14 U.S.)
28.4 W/m^2*K for windows and doors for winter (R0.20 U.S.)
25.8 W/m^2*K for walls and roof for summer (R0.22 U.S.)
19.6 W/m^2*K for windows and doors for summer (R0.29 U.S.)
- Window-Wall-Ratio: 0.15 on average
  - 0.24 for south
  - 0.08 for north
  - 0.14 for east
  - 0.13 for west

2. Internal Load

(1) Heat

- 4 persons: 291.12 watt of sensible heat, 234.42 watt of latent heat
- Lighting fixtures: 610 watt of sensible heat
- Miscellaneous: 560 watt of sensible heat
- Cooking: 8,219 watt of sensible heat, 1,450 watt of latent heat
- Refrigerator: 1500 watt of sensible heat
- Hourly fraction is applied to calculation of internal heat gain

(2) Moisture

- 5~6 liters/day by 4-persons (respiration + perspiration)
- 10 liters/day by cooking, cleaning, etc by family size-4
- Hourly fraction is applied to calculation of internal moisture gain

Time of Day	Heat Gain (Watt)		Moisture Gain (ml)	Time of Day	Heat Gain (Watt)		Moisture Gain (ml)
	Sensible	Latent			Sensible	Latent	
0-1	829.99	210.96	360	12-13	1,436.57	87.61	675
1-2	829.99	210.96	330	13-14	821.58	58.60	450
2-3	829.99	210.96	315	14-15	464.59	58.60	420
3-4	829.99	210.96	315	15-16	416.78	58.60	465
4-5	852.39	210.96	315	16-17	416.78	58.60	855
5-6	818.79	210.96	390	17-18	1,427.94	356.01	960
6-7	1,447.79	210.96	570	18-19	1,440.14	356.01	960
7-8	2,882,36	312.50	885	19-20	1,490.15	341.51	780
8-9	2,966.35	327.00	840	20-21	1,160.4	210.96	750
9-10	1,939.38	58.60	900	21-22	1,784.2	210.96	825
10-11	1,776.58	58.60	885	22-23	1,746.59	210.96	660
11-12	1,759.97	87.61	675	23-24	982.59	210.96	405

Daily Internal Heat and Moisture Gain Profile

3. Infiltration

- 0.3 ACH for all day

4. Weather Data

- TMY2 data for Detroit, Michigan for tow seasons: winter (Jan. 27 ~ Feb. 01), summer (Jul. 03 ~ Jul. 08)

5. Thermal Control System

- Heat Supply: 9,000 Watt (≈ 30,729 Btuh) by convective system
- Heat Remove: 10,000 Watt (≈ 34,144 Btuh) by convective system
- Moisture Supply: 1.41 Kg/hr
- Moisture Remove: 2.36 Kg/hr