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Building Space Thermal Control Model Responding to Sharp Changes in Outdoor Temperature

Sangchul KIM, Jonghoon AHN*

Abstract: As computing and data-driven technologies have improved, the precision of the building thermal control models has been gradually improved, but the use of energy resources to operate them has been also increased. It is imperative to investigate the optimized point of energy use and human comfort for their thermal control strategies. The aim of this research is to find an energy-efficient thermal control model to maintain the constancy of thermal comfort and suppress the increase of energy use in association with precise environmental controls. Based on a cooling and heating air supply model in a simplified building model, a comprehensive energy use pattern is confirmed by adding an adaptive control model that allows indoor thermal comfort to be maintained at a setting level. The adaptive control model utilizing the artificial neural network and the adjustment process of initial settings is proposed to examine its performance in controlling the amount of thermal supply air and its temperature. For the clear comparison between a baseline model and a proposed model, the statistical indices of each thermal dissatisfaction value and the weekly heating energy use are utilized. The results of this research show that the thermal dissatisfaction fluctuation is alleviated by about 22.0~41.0% and the energy efficiency is improved by about 5.1%, respectively. The results provide the effectiveness of the proposed model which can improve both the energy use and thermal comfort in a building space. This advantage can help old thermal systems to improve their usability without replacing any major components.

Keywords: adaptive process; artificial neural network; building space; energy use; thermal comfort

1 INTRODUCTION

To control the Heating, Ventilating, and Air-Conditioning (HVAC) systems, several control models have been improved by the investigation of system design methods and operational strategies. Through different viewpoints of mathematical and statistical approaches, many systems have been investigated to optimize their performance of boilers, chillers, exchangers, fans, duct works, and operational schedules [1, 2]. Such diversified control models for the components have been examined in the field where building internal algorithms to define their patterns is not relatively complicated. Based on experimental data, the improvement of the control algorithms or data dealing methods by a little of parameters and simple calibration have resulted in the conventional systems to optimize their performance [3, 4].

The fast growth of machines and equipment comes to require more precise control rules or algorithms to effectively deal with their complex and sensitive operational conditions. Various computing devices have been installed in most buildings to use data-driven methods that inevitably results in complex calculations. To find appropriate ways to respond, the Fuzzy Inference System (FIS) and Artificial Neural Network (ANN) have been utilized in ambiguous and complex situations where intuitive solutions are hard to find.

The FIS is an effective deterministic algorithm in the fields where exact numbers were not easily determined due to model's subjectivity. Many different types of membership functions in the FIS have been adopted to define appropriate values of output levels for fuel use, air supply, and water flow in thermal systems [5, 6]. Its inner structure dealing with ambiguous situations was an effective method to investigate the performance of complex problems such as analyses of radiation, convection, ventilation, and infiltration effects. In the field of deterministic models, the FIS has been frequently utilized to define more reliable output signals reflecting both of the subjective and objective variables [7, 8].

The ANN model was developed to deal with hidden correlations of several variables. Before using the model, some variables in regression models were frequently regarded so that there was no any clear correlation between them. That is because there were not effective calculation systems to deal with the huge data. With the help of the ANN algorithm and the advanced hardware, many researchers can utilize their computational methods to solve these complex problems [9, 10]. Various numerical corrections should be made in the development of a module itself for elements constituting a building, such as an outer wall, a window, a roof, and a floor. And some result errors and residuals can be found when independently generated computational modules were combined into one model. Various issues of combining were found in the process of correcting and supplementing existing experimental and practical thermal models rather than creating a new one. To solve the mathematical and statistical issues, the ANN has suggested convenient ways for retrofitting by analyzing as many hidden correlations [11, 12]. The ANN has shown the advantage of appropriately responding to inputs that are associated with various factors that are difficult to specify, such as regional and climatic characteristics, which must be considered in architectural models. Several studies have been developed to effectively deal with hidden correlations of the major variables, such as orientation, precipitation, and terrain conditions, to investigate on the energy issues [13, 14].

As the building thermal systems have been modernized and complicated, the assessment of indoor thermal comfort which seems to be difficult to quantify has been diversified by use of mathematical approaches. To increase the objectivity of various types of survey-based results, the Predicted Mean Vote (PMV) was frequently used. To complement the PMV index, the Predicted Percentage of Dissatisfied (PPD) was also preferred. These indices dealing with major thermal conditions and human factors have been developed as the architectural and user characteristics were regularized by the increases in experimental data and simulated genetic algorithms [15, 16]. By using the methods, several assumptions and design scenarios were tested to define better rules of tuning algorithms for the comfort models [17].

The FIS and the ANN algorithms have been adopted in the PMV models to supplement inner interactions between simulation configurations and operational processes. For the improvement of the conventional control rules, numerical changes in occupant conditions by design assumptions such as types of works and clothes were utilized to analyze specific thermal situations associated with mechanical supply systems for cooling and heating air [18, 19]. Additionally, data-driven genetic algorithms were used to improve specific regression models in the FIS model for making structure realistic, and, by means of instantly connecting user responses, adaptive structure in the ANN was utilized to improve their statistical significance of learning algorithms. In the case of learning models, research results that improve indoor thermal comfort levels by more than 3-8% compared to conventional thermostat models were confirmed, but these learning models are based on limited conditions including building geometries and operation strategies [20-22].

However, there have not been more effective studies on either the energy efficiency or the control precision in specific and unexpected situations to maintain the desired performance of thermal systems. Moreover, as the time period of testing the model increases, several weaknesses of the models have been confirmed, that the outliers and residuals increase against the initial expected experimental and simulated results. Therefore, it is imperative to test an efficient controller and an adaptive process, and how the model effectively works to reduce possible errors and residuals in some unexpected changes in outdoor conditions. In this regard this research explores how thermal comfort and energy use change by adding a simple adaptive module for heating and cooling air supply controls. This aims to find a sustainable way to increase the efficiency of the entire system simply by adding some modules without entirely retrofitting of existing thermal systems.

Nomenclature	
A	area of material(s) / m^2
Cv	specific heat capacity at constant volume / J/kg·K
Cp	specific heat capacity at constant pressure / J/kg·K
D	thickness of material(s) / m
G	thermal conductance / W/K
h_{in}, h_{out}	convection heat transfer coefficient inside, outside / W/m^2·K
k	thermal conductivity / W/m·K
$\dot{m}_{ht}$	mass flow-rate from system / kg/h
$\dot{m}_{in}$	mass flow-rate inside room / kg/h
$\dot{m}_{out}$	mass flow-rate outside room / kg/h
m_{rm}	mass flow-rate in room air / kg
Q_{loss}	heat loss by convection and transmission / J
Q_{gain}	heat gain by convection and transmission / J
R	thermal resistance / K/W
T_{ht}	air temperature from heater / °C
T_{out}	outdoor temperature / °C
T_{rm}	room temperature / °C
T_{set}	set-point temperature / °C
U	internal energy / J
W	work / J

2 METHODOLOGY
2.1 Overall Framework

The simulation model in this research consists of six independent processes such as signal generating, adaptive signal generating, thermal comfort detecting, thermostat adjusting, supply air controlling, building load calculating. The resulting value of a previous process is input into a next process to calculate a signal value, which in turn is fed back to produce the adjusted value or signal of the first process. The model utilizes a weather data and templates of New York City, USA from March 21st to 28th in the website of Energy Plus by the US Department of Energy.

Table 1 Parameters of building geometries and thermal factors

Parameter		Unit	Value
Type		-	Small-sized Office (2F)
Width × Depth × Height		m	20.0 × 15.5 × 3.3
Roof	Area	m^2	310.0
	Thermal Resistance	K/W	1.16×10^{-2}
Wall	Area	m^2	223.0
	Thermal Resistance	K/W	5.76×10^{-3}
Window	Area	m^2	12.0
	Thermal Resistance	K/W	2.14×10^{-3}

Fig. 1 and Tab. 1 summarize the main information of the building model used in this research. The two-story building model includes six spaces and thermal zones: one office room at each floor, one hall at the first floor, one small-sized meeting room at the second floor, one restroom at each floor. The model calculates its heating and cooling energy transfer between inside and outside through the building envelopes and comfort levels reflecting *Trm* derived from the energy transfer results. The thermostat model works as a baseline model to define the performance of the fuzzy-based and network-based models in terms of energy use and thermal comfort.

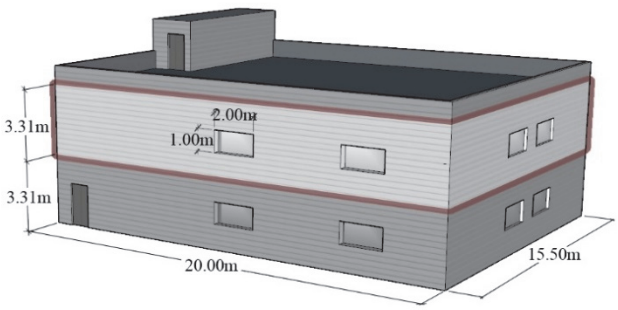

Figure 1 Schematic building model

For adaptive thermal controls, this research utilizes an independent adaptive network-based model. The PMV value after indoor thermal control is out of the range of a setting value ($-0.5 < x < 0.5$), an adaptive comfort module adjusts *Tset*. Then, after the adaptive control is executed, the PMV value is still out of the ranges, it repeats the process. However, if the PMV value is within the initial setting value at any simulation processes, this process is carried out without any additional change of *Tset* [23, 24].

This process can be summarized as follows:

1) An ANN control model is trained by use of the output signals from the FIS model as inputs from the average temperature data over the past 30 years in seven climatic zones.

2) From the results of the serial process of Signal Generator, Thermostat, Controller, Heating/Cooling Supply, and Building modules, the proposed model calculates the PMV/PPD value again.

3) If the PMV value is out of the initial range of *Tset*, an adaptive model sends a signal which adjusts the thermostat setting to ±1 °C step to supplement the PMV value. If the PMV value is defined within the range, the thermostat setting is adjusted to ±0.1 °C step to reduce its energy use.

4) After the simulation of one cycle, if the PMV value is still out of range, the adaptive model adjusts the thermostat setting to ±2°C step to supplement the PMV value.

5) In any phase, if the PMV value deteriorates due to the adjustment of ±0.1°C step to reduce its energy use, the process for reducing its energy use does not operate.

6) This cycle from 1) to 5) is repeated for a specified simulation period such as day, week, month or year.

2.2 Thermal and Comfort Models

From the thermodynamic first law, the total heat loss and heat gain through the envelopes are given by [25]:

$$Q_{\mathrm{loss}} + Q_{\mathrm{gain}} = \frac{\mathrm{d}u}{\mathrm{d}t} \tag{1}$$

where, Q_{loss} is the heat loss through walls, a roof, windows and doors, Q_{gain} is the heat gain from a heater or a cooler, u is the internal energy, and t is the time.

From the heat conduction transfer through the envelopes, the heat loss of the building space, Q_{loss}, is given by:

$$Q_{\mathrm{loss}} = \frac{T_{\mathrm{rm}} - T_{\mathrm{out}}}{\left\{\dfrac{1}{(h_{\mathrm{out}}A)} + \dfrac{D}{(kA)} + \dfrac{1}{(h_{\mathrm{in}}A)}\right\}} \tag{2}$$

where, T is the temperature, h_{out} and h_{in} are the heat transfer coefficients outside and inside, k is the transmission coefficient, A is the area, D is the thickness of the envelopes.

From the enthalpy and the mass flow rate, assuming that there is no work in the system, heat gain transfer of the building space, Q_{gain}, is given by [25]:

$$Q_{\mathrm{gain}} = \dot{m}_{\mathrm{ht}} C_p (T_{\mathrm{ht}} - T_{\mathrm{rm}}) \tag{3}$$

where, $\dot{m}_{\mathrm{ht}}$ is the mass flow-rate from system, and C_p is the specific heat capacity at constant pressure.

The rate of internal energy is given by:

$$\frac{\mathrm{d}u}{\mathrm{d}t} = m_{\mathrm{rm}} C_v \frac{\mathrm{d}T_{\mathrm{rm}}}{\mathrm{d}t} \tag{4}$$

where, m_{rm} is the mass flow-rate in room air, and C_v is the specific heat capacity at constant volume.

From the processes, the time derivative of T_{rm} is rewritten by:

$$\frac{\mathrm{d}T_{\mathrm{rm}}}{\mathrm{d}t} = \frac{1}{m_{\mathrm{rm}} C_v} * \left(\left(\frac{T_{\mathrm{rm}} - T_{\mathrm{out}}}{\dfrac{1}{h_{\mathrm{out}}A} + \dfrac{D}{kA} + \dfrac{1}{h_{\mathrm{out}}A}} \right) + \left(\dot{m}_{\mathrm{ht}} C_p \left(T_{\mathrm{ht}} - T_{\mathrm{rm}} \right) \right) \right) \tag{5}$$

Several references have utilized the equation of the PMV developed by Dr. Fanger to calculate the theoretical values of indoor thermal comfort, and the PPD equation can be derived from the PMV model as follows [26, 27].

$$PMV = 3.155\left(0.303\mathrm{e}^{-0.114M} + 0.028\right)L \tag{6}$$

$$PPD = 100 - 95\mathrm{e}^{\left(-0.03353 PMV^4 - 0.2179 PMV^2\right)} \tag{7}$$

where, M is metabolic rate, and L is thermal load.

For M and L, the PMV equation uses many factors such as the respiratory convective heat exchange, the clothing insulation, the ratio of clothed surface area, the mean value of the surface temperature of clothed body, the localized average air speed, and saturated humidity ratio at the skin temperature [26, 27].

2.3 Control Models

The baseline model utilizes the rule of typical commercial thermostat for comparative analyses with the setup of control dead-band, ±1 °C, which means that the thermostat sends turn-on or turn-off signal for the air supply model if the difference between T_{set} and T_{rm} is larger than ±1 °C.

The FIS uses two different input values to control the amount of supply air and its temperature. The temperature difference between T_{set} and T_{rm} is specified as E, wherein the differences between E_n and E_{n-1}, the derivative of the temperature difference, is specified as ΔE in the FIS membership function.

$$E = T_{\mathrm{set}} - T_{\mathrm{rm}} \tag{8}$$

$$\Delta E = \frac{\left(E_n - E_{n-1}\right)}{\Delta t} \tag{9}$$

The membership function calculates one output signal for two different models with the values of discourse 0 (0%) to 1 (100%) for the amount of supply air and –5 °C to 5 °C for its temperature, respectively. Inside its inner process, the first layer which consists of two inputs #1 and #2 supplies the values to the next, then, the triangle membership function works to calculate the output value with a maximum equal to value 1 and a minimum equal to value 0 within the specified ranges of x [28, 29].

$$\text{if } x \text{ is } A \text{ and } y \text{ is } C \text{ then } f_1 = p_1 x + q_1 y + r_1 \tag{10}$$

$$\mu(x) = \text{triangle}(x; a_i, b_i, c_i) = \begin{cases} x \le a_i \to 0 \\ a_i \le x \le b_i \to \dfrac{(x - a_i)}{(b_i - a_i)} \\ b_i \le x \le c_i \to \dfrac{(c_i - x)}{(c_i - b_i)} \\ c_i \le x \to 0 \end{cases} \tag{11}$$

The intersections of each expression, such as Big-Positive (over 1), Small-Positive (0~1), Neutral (0), Small-Negative (–1~0), Big-Negative (under –1) for E, and Very-Positive (over 2), Positive (1~2), Neutral (1), Negative (–2~–1), Very-Negative (under –2) for ΔE, occur at an interval. For instance, the fuzzy membership function for the amount of mass sends the signals as a Small-Positive when a value of E was detected as 0.44, and as a Very-Negative when a value of ΔE was detected as –2.3, respectively. Then the algorithm interprets the signals in the membership function matrix to turn off for the amount of air and to increase the air temperature, by these two independent control outputs. As a principle, the ANN algorithm includes a large class of several structures, and the optimized selections of a nonlinear mapping function x with a network are required as described in Fig. 2 [30, 31].

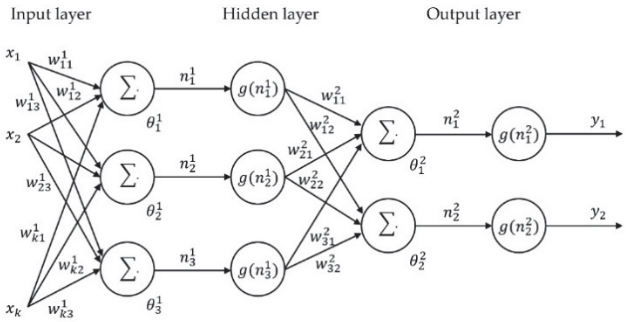

Figure 2 Diagram of the artificial neural network

In this research, the inner structure in function approximation consists of two input layers, 1ten hidden layers, and one output layer for the amount of air and its temperature, respectively. The inputs of Eq. (12), $x_1, \ldots, x_k$, to the neuron are multiplied by weights w_{ki} and summed up with the constant bias term θ_i., and the resulting n_i is the input to the activation function g [32, 33]. The input layers are set up as E and ΔE from the difference between T_{set} and T_{rm}, and they are trained to find better control outputs to meet the appropriate value of the PMV within the initial setting range ($-0.5 < a < 0.5$). For its simulation configuration, a scale conjugate gradient algorithm is used, and the repetition of simulations is executed up to 1000 times to get valid regression results [34, 35]. From the simulation results for the statistical significance, the R^2 values were confirmed as 0.99034 for controlling the amount of supply air mass and 0.98610 for controlling its temperature, respectively. These values can be regarded to be very effective in relation to the maintenance of thermal comfort and the reduction of energy use.

$$n = \sum_{i=1}^{K} x_i \omega_i - \theta \tag{12}$$

$$\delta_k(p) = \frac{\vartheta y_k(p)}{\vartheta n_k(p)} \times e_k(p) \tag{13}$$

2.4 Simulation Model

Fig. 3 displays the proposed simulation block model, which consists of six independent modules of Signal Generator, Adaptive, Comfort, Thermostat, Cooling/Heating Control, and Building. This model calculates indoor temperature, energy use, and PMV/PPD value at every one minute, and also, an adaptive process responding to the thermal comfort value adjusts *Tset* of the thermostat at each simulation term to reduce energy use in association with maintaining thermal comfort. The module of Cooling/Heating Control is replaced at each simulation execution by the thermostat, FIS, and ANN algorithms built separately in each case. Because the Adaptive module is derived from the separated learning process of ANN, it is connected only when the ANN controller is tested to define the performance of ANN algorithm. By use of the above equations, Signal generator, Adaptive, Comfort, Thermostat, Building modules were modelled using MATLAB program, and the fuzzy logic and ANN modules in Control were modelled with some parameters modified based on the available apps in MATLAB such as Fuzzy Logic Designer and Neural Net Fitting. In addition, most parameter setting values were adopted from the templates of Energy Plus.

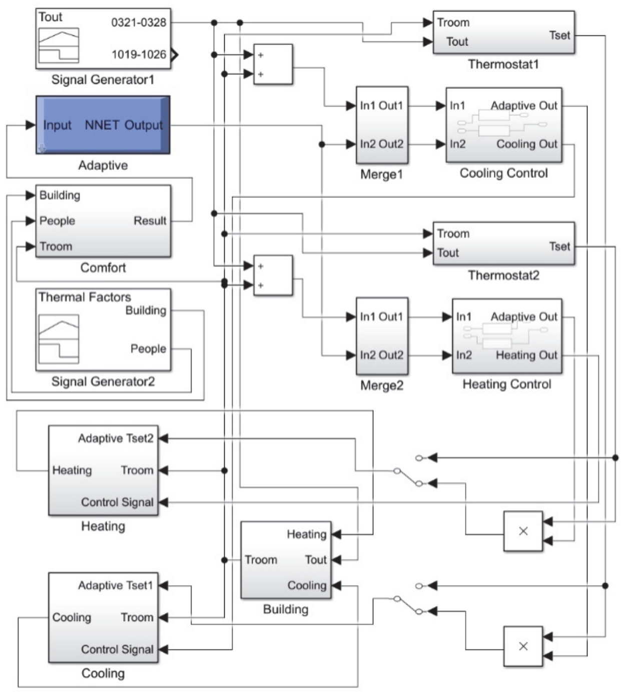

Figure 3 Simulation block model

3 RESULTS
3.1 Room Temperature by the Control Models

Figs. 4, 5, and 6 display *Tout* at New York City from March 21st to 28th, and the results of *Trm* are controlled by three different models of thermostat, FIS, and ANN. As shown in Fig. 4, it is confirmed that the thermostat model, which operates only within a predetermined temperature range, operates constantly throughout the entire simulation period. As described in Fig. 5, it can be verified that the FIS model significantly reduces the deviation of control variations compared to the thermostat model throughout most of the simulation period. In addition, it shows more effective *Trm* maintenance performance even in the periods of the 24th, 25th, and 26th, when the outdoor temperature pattern changes sharply. However, since a relatively inefficient response is confirmed to the sharp temperature change below 3 °C, it may be necessary to supplement the FIS membership function at a low *Tout*.

As confirmed in Fig. 6, the ANN model shows very effective *Trm* control performance throughout the entire simulation period. This implies a fact that the ANN algorithm built through typical Tout changes can be effectively responding to unexpected sharp temperature changes. In addition, in the deterministic model, FIS, where control signals are transmitted by calculating in real time after the external condition of *Tout* was given, it is confirmed that the overshooting and the fluctuations of the control pattern are not completely controlled. In the case of ANN, the overshooting and the fluctuations that may appear in the entire period are effectively controlled, even though an adaptive model reflecting the PMV value was additionally working. Further analysis will be needed as to whether the operation of the adaptive model for the thermal comfort and energy conservation has occurred according to the calculation of the PMV value.

3.3 Heating Energy by the Control Models

The previous Figs. 4, 5, and 6 on the *Trm* control pattern are directly connected to the aspect of each model's energy use. As illustrated in Fig. 7, when the indoor temperature falls below *Tset*, the thermostat sends a signal to start heating and to supply more than 100 MJ of energy. And, when the *Trm* reaches the *Tset*, the heating process is turned off and energy supply is not required. On the other hand, the FIS model in Fig. 8 shows effective control patterns to reduce overshooting. To be precise, the overshooting was also reduced, but it can be interpreted as effectively reducing the maximum energy demand in situations where the heating energy from 106 to 108 MJ is not required. This can be interpreted as an evidence for confirming that the indoor thermal comfort reaches a sufficiently valid area even if energy is not supplied to the dead-band of the thermostat. In Fig. 9, it is confirmed that the ANN model supplies heating energy in almost the opposite pattern to the graph of *Tout*. This is expected to have a great effect on more sustainable maintenance for the hardware of thermal systems by the mitigation of unnecessary overshooting and maximum capacity.

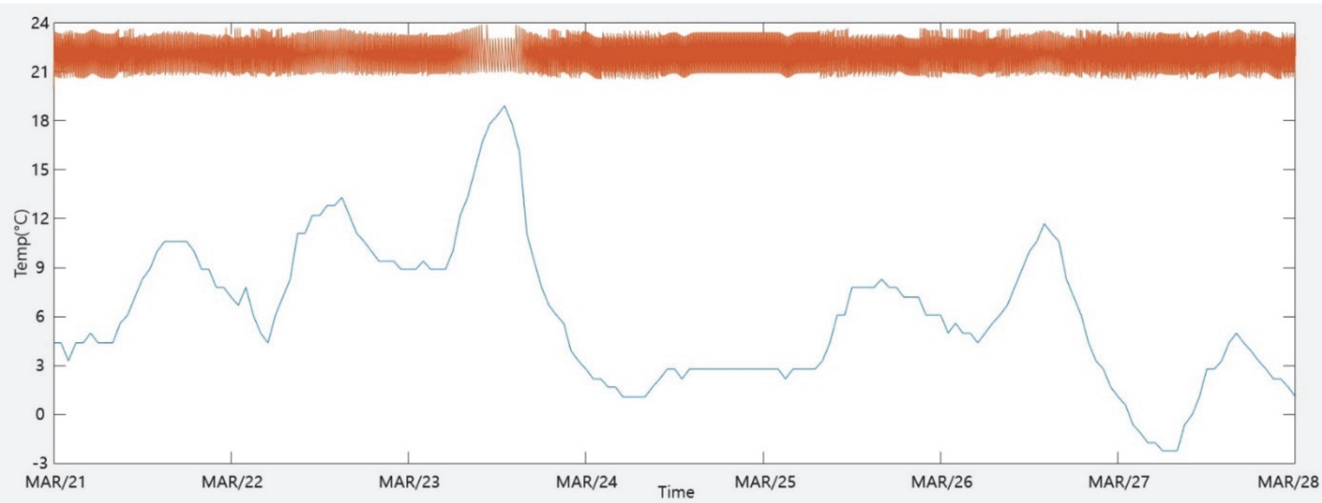

Figure 4 *Trm* controlled by the thermostat

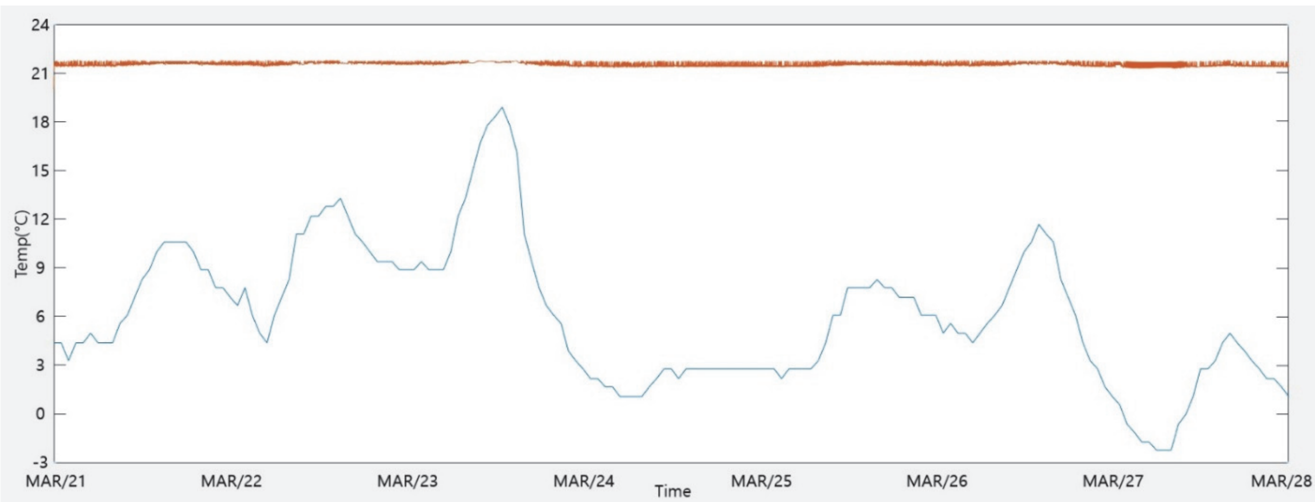

Figure 5 *Trm* controlled by the FIS model

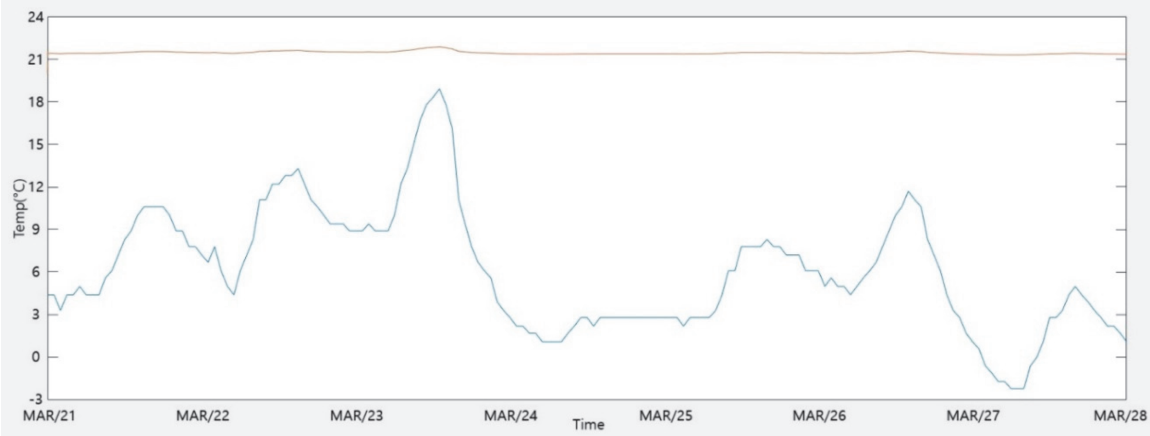

Figure 6 *Trm* controlled by the ANN model

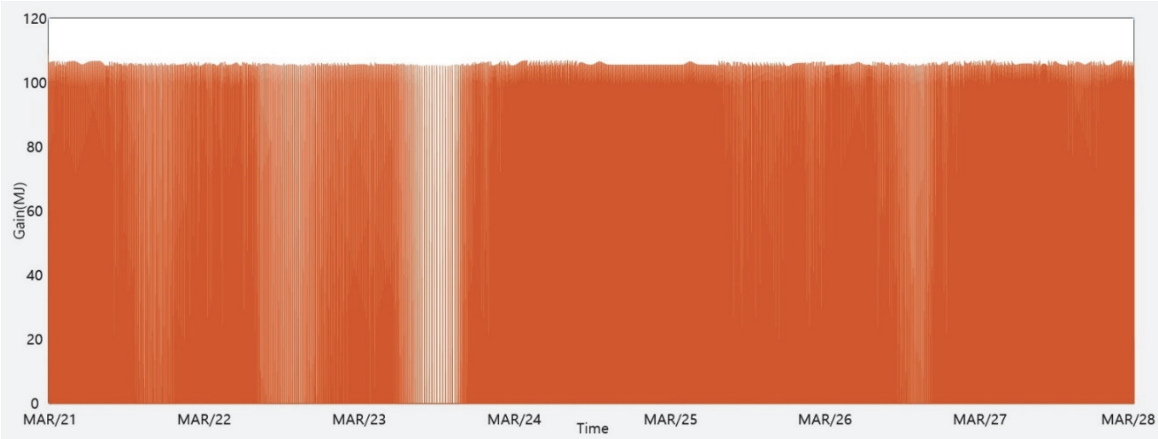

Figure 7 Heating energy controlled by the thermostat

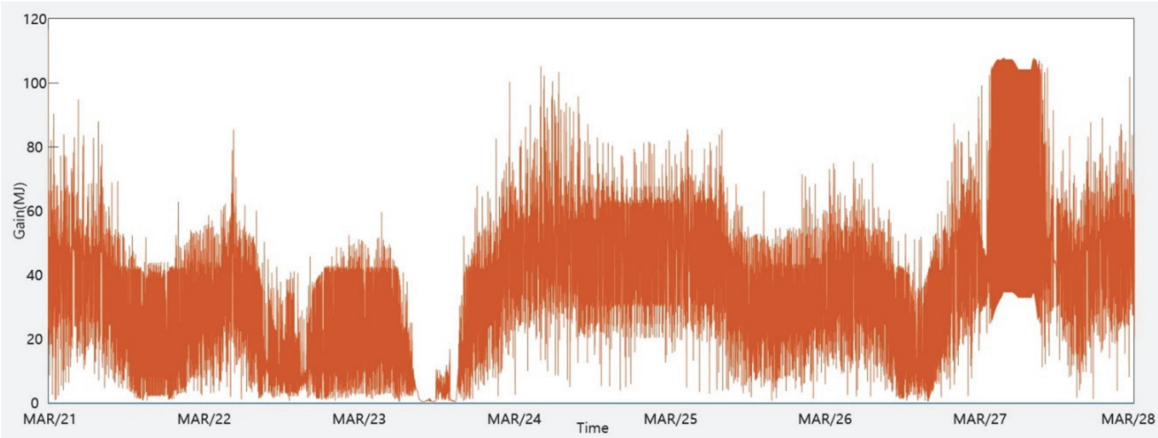

Figure 8 Heating energy controlled by the FIS model

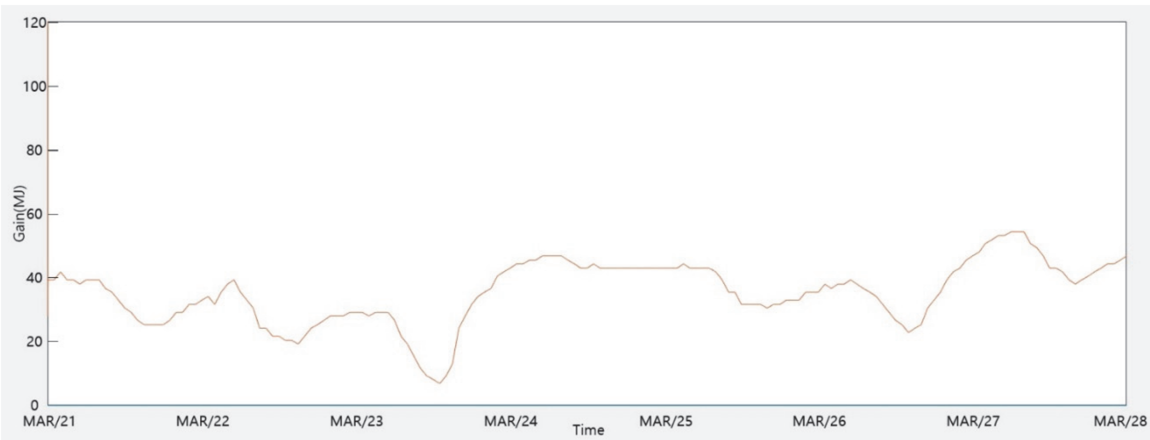

Figure 9 Heating energy controlled by the ANN model

The advantage of the ANN model was more pronounced on the night time of March 27th, when a sharp descent temperature pattern was made compared to the previous dates. The thermostat model is a simple model that supplies energy until it reaches *Tset*, so relatively more dense energy supply patterns were executed. The FIS model is found to be sending relatively inefficient output signals compared to other dates, resulting in a continuous maximum output of 106 to 108 MJ of energy similar to the thermostat during the night time of March 27th. It may be assumed that the control effect is degraded as the temperature difference of E and the derivative of the temperature difference of ΔE are continuously calculated as the maximum value or a value outside the maximum value range in the setting of the membership function of FIS. On the other hand, it is confirmed that ANN has no time range over 60 MJ for the entire simulation period, and it can be seen that the maximum overshoot values are significantly alleviated even in the time, where overshoots occurred particularly in the previous two models. This can serve as a basis for how much energy use the ANN model can mitigate in the dead-band sections of the thermostat model at night, thereby suggesting a methodology that can reduce the maximum capacity and various resources in the thermal system design. However, compared to the other two models, it is confirmed that the ANN model is continuously operated during the entire simulation period without turning off, and it is necessary to analyze how much energy use has been increased or decreased. Tabs. 2 and 3 summarize comparative analyses of thermal and energy performances for three different control models by use of the standard deviation of the PPD and weekly heating energy use. In terms of thermal dissatisfaction as the PPD, calculating the standard deviation based on 0% can be regarded as an effective indicator in maintaining constancy of thermal comfort levels.

Table 2 Comparison of the thermal comfort by the controllers

Controller	PPD		PMV	
	Std. Deviation	Reduction / %	RMSE	Reduction / %
Thermostat (Baseline)	28.67	N/A	0.59	N/A
FIS	18.81	34.4	0.54	8.5
ANN	16.92	41.0	0.46	22.0

Table 3 Comparison of the energy use by the controllers

Controller	Weekly Energy Use / kWh	Reduction / %
Thermostat (Baseline)	20.67	N/A
FIS	19.67	4.9
ANN	19.64	5.1

As indicated in Tab. 2, the ANN model shows significantly improved performance of maintaining constancy of thermal comfort compared to the thermostat and the FIS models. In the case of PMV, the root mean square error can be utilized because it can be assumed as a best-fit model to maintain the values close to zero for the entire simulation period. Calculating the values of each model further reveals the advantage of ANN model to maintain the constancy of thermal comfort, which demonstrates a performance improvement of about 22% over baseline thermostat model. However, as shown in Tab. 3, the ANN model reduced energy consumption by about 5.1% and about 0.2%, respectively, compared to the thermostat and the FIS models. It can be assumed that these relatively small differences in energy consumed were derived from its precise control by optimizing the overshooting value generated when the *Trm* reached the *Tset*. In the simulation tests conducted with similar methodologies and models, thermal comfort and energy use show the control efficiency by 6~14% and 2~39%, respectively [14, 17, 31]. However, since this model tests an adaptive model using additional modules to maintain the quality of comfort in existing control systems, the energy use savings of about 5% can be sufficiently significant. This result can be changed by the validation setting of the ANN learning process if the simulation interval is further reduced or slightly increased. In fact, when the simulation interval was set to 15 minutes (an energy simulation application default setting value), the energy use was increased more than 10%. Therefore, effectively setting the range of time intervals in which this control algorithm is implemented should also be one of the main follow-up studies. Regarding the result, although this model has significant advantages over deterministic models in maintaining the constancy of thermal comfort, it can be concluded that for the energy performance, it needs to be found in terms of optimizing thermal system capacity rather than simply reducing energy use to operate. It implies the fact that the proposed model can be used to effectively control thermal environment for subjective human activities in relatively large scaled buildings responding to the unexpected sharp changes of outdoor temperatures.

4 CONCLUSIONS

The aim of this research is to investigate the effectiveness of a network-based building thermal control model of learning and adaptive algorithm in terms of improving or maintaining the constancy of thermal comfort and energy efficiency. By comparison with a conventional thermostat and fuzzy-based controllers, the performance of the proposed control process was confirmed by about 22.0~41.0% improvement for thermal dissatisfaction and by about 5.1% decrease for heating energy use. Conclusively, the proposed model confirmed that the network-based learning process appropriately responded to specific situations where unexpected sharp temperature changes occur.

The significance of this proposed control model can be summarized as follows. First, it can be used to determine control rules that apply accurately to various and unexpected weather situations for mixed-use buildings that adopt complex thermal systems, or large-scaled buildings that are used by a huge number of unspecified visitors, such as airport terminal, hospital, hotel, and distribution center. In addition, controlling overshooting that may occur due to sharp changes in the external environment could enable capacity saving in the system design or help to extend the life cycle of each hardware in thermal systems.

However, it will help to increase the statistical significance in the learning process if more data, such as more cities and periods, are used in defining regression models. As a consequence, some follow-up studies will be conducted to reinforce and supplement the characteristics of the models proposed in this research. They may include modelling using building data of various uses and sizes, a comprehensive survey on the qualitative thermal comfort of users, and genetic algorithms based on experimental studies to increase statistical validity.

Acknowledgments

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Contact information:

Sangchul KIM
School of Architecture and Design Convergence,
Hankyong National University,
Anseong, South Korea, 17579
E-mail: sckim08@hknu.ac.kr

Jonghoon AHN
(Corresponding author)
School of Architecture and Design Convergence,
Hankyong National University,
Anseong, South Korea, 17579
E-mail: architectism@hknu.ac.kr